Renewable and Sustainable Energy Reviews 34 (2014) 409–429

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

A review on optimized control systems for building energy and comfort management of smart sustainable buildings

Pervez Hameed Shaikh*, Nursyarizal Bin Mohd Nor, Perumal Nallagownden, Irraivan Elamvazuthi, Taib Ibrahim

Universiti Teknologi PETRONAS, Department of Electrical and Electronics Engineering, Bandar Seri Iskandar, 31750 Tronoh, Perak, Malaysia

A R T I C L E I N F O

Article history:
Received 26 December 2013
Received in revised form
18 February 2014
Accepted 7 March 2014
Available online 30 March 2014

Keywords:
Building
Energy
Comfort
Control
Optimization
Management
Occupants

A B S T R A C T

Buildings all around the world consume a significant amount of energy, which is more or less one-third of the total primary energy resources. This has raised concerns over energy supplies, rapid energy resource depletion, rising building service demands, improved comfort life styles along with the increased time spent in buildings; consequently, this has shown a rising energy demand in the near future. However, contemporary buildings' energy efficiency has been fast tracked solution to cope/limit the rising energy demand of this sector. Building energy efficiency has turned out to be a multi-faceted problem, when provided with the limitation for the satisfaction of the indoor comfort index. However, the comfort level for occupants and their behavior have a significant effect on the energy consumption pattern. It is generally perceived that energy unaware activities can also add one-third to the building's energy performance. Researchers and investigators have been working with this issue for over a decade; yet it remains a challenge. This review paper presents a comprehensive and significant research conducted on state-of-the-art intelligent control systems for energy and comfort management in smart energy buildings (SEB's). It also aims at providing a building research community for better understanding and up-to-date knowledge for energy and comfort related trends and future directions. The main table summarizes 121 works closely related to the mentioned issue. Key areas focused on include comfort parameters, control systems, intelligent computational methods, simulation tools, occupants' behavior and preferences, building types, supply source considerations and countries research interest in this sector. Trends for future developments and existing research in this area have been broadly studied and depicted in a graphical layout. In addition, prospective future advancements and gaps have also been discussed comprehensively.

© 2014 Elsevier Ltd. All rights reserved.

Contents

* Corresponding author. Tel.: +60 14 9971 034.
E-mail address: engr.pervezhameed@gmail.com (P.H. Shaikh).

http://dx.doi.org/10.1016/j.rser.2014.03.027
1364-0321/© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

1.1. Building energy scenario

The world's predominant fossil resources are at the verge of depletion due to the enormous usage of energy resources in the last two decades. Therefore, concerns over changing climatic conditions (i.e. global warming, depletion of ozone layer, etc.), energy security, and adverse environmental effects are growing among governments, researchers, policy makers, and scientists in developed as well as developing countries. The International Energy Agency (IEA), in regard to the current energy scenario, has raised the concerns for environment, energy security and the economic prosperity generally known as (3Es) [1]. However, the European union (EU) describes energy-cut objectives until 2020 [2]: (i) the EU GHG emissions reduction should be at least 20% below the levels of 1990, (ii) renewable energy contribution of a minimum 20% in the energy consumption of EU and (iii) primary energy usage would be reduced to 20% in comparison to anticipated levels through energy efficiency measures. Moreover, almost like targets and even much restricting in some cases have been specified by the US policy of energy efficiency and conservation [3].

Globally, the challenge of the growing energy demand in buildings is mysterious. Buildings account for more than one-third of the total primary energy supply. The building energy consumption in selected countries is shown in Fig. 1. Since, 40% of the world's energy is being consumed in buildings ultimately, it accounts for 30% of the CO_2 emissions, as given in Table 1. The CO_2 emissions of some selected countries available in the literature indicate that the USA being the largest emits approx. 40–48%. On an average, the potential savings of approximately 30% could be achieved as in Table 1 through the intelligent automation in buildings. In context to that, the World Business Council for Sustainable Development (WBCSD) in 2009 conducted a research that found that the energy usage in buildings could be cut dramatically providing a saving of as much as the entire transport sector uses currently [4].

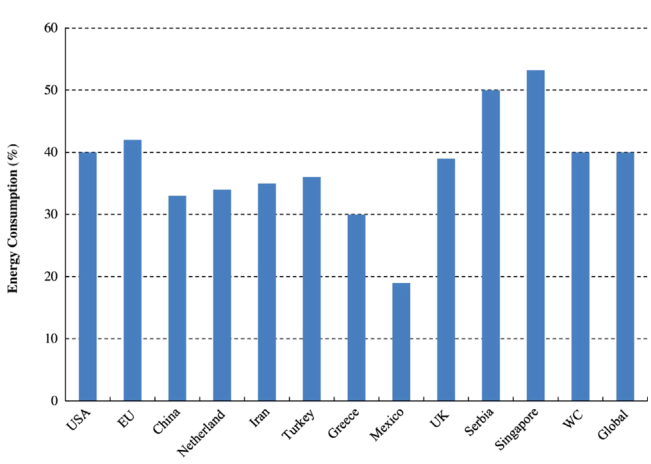


Fig. 1. Building energy consumption in selected countries.

Therefore, the saving of building energy consumption and wastage is significant, since, it helps to preserve the finite fossil resources, lower the energy cost for consumers and business, thus allows building sustainability. Besides, the contribution of renewable resources in buildings is likely to be constrained due to various limitations. In such circumstances, efficient management of building energy plays a vital role to achieve a low carbon economy and sustainability possibly at a faster rate. Energy efficient buildings, which facilitate intelligent building control, are becoming the trend for the future generation of buildings.

1.2. Indoor building comfort

Buildings are generally built for human's habitation. Moreover, approx. 90% of people spend most of their time in buildings [5]. Indoor comfort plays a significant role and poses a huge impact to preserve inhabitant's health, morale, working efficiency, productivity and satisfaction [6]. There has been an increasing demand by inhabitants for the improvement of indoor environmental comfort, whilst reducing energy consumption and CO_2 emissions during the previous decade.

Therefore, an energy and comfort management system (ECMS) must be comprising intelligent control systems for buildings, which uses computers, microprocessors, storage devices and communication links [7]. The main aim of an ECMS is to fulfill the occupant's expected comfort index whilst reducing energy consumption with regard to the energy price variation during the operation of building. ECMS commonly requires functions including indoor comfort parameters (classified in multiple categories and the most significant are thermal, humidity, indoor air quality and illumination levels), occupant preference and electrical energy control. Ensuring the comfort index, generally defined as the condition of the mind, which articulates satisfaction of environmental conditions, is due to human psychological effects. In various cases, people may decline to work or live in a particular

Table 1
Building energy consumption and GHG emission with saving potential in selected countries and world.

Sr. #	Country/ region	Building energy consumption (%)	CO_2 emissions (%)	Potential saving (%)	Reference
1	USA	40	40–48	20	[24,39,40,54]
2	European Union	40–42	35–40	27–30	[25–27,41]
3	China	33	–	–	[28–30]
4	Netherland	34	–	–	[61]
5	Iran	35	–	–	[31]
6	Turkey	36	32	30	[32,33]
7	Greece	30	40	–	[34]
8	Mexico	19	–	–	[118]
9	United Kingdom	39	–	–	[35]
10	Serbia	50	–	20	[36,37]
11.	Singapore	53.2	21.4	–	[42,229]
11	Western countries	40	–	–	[38]
12	Global	40	30	5–30	[22,23]

Nomenclature

AAP	April agent platform
AMPL	a mathematical programming language
ANFIS	adaptive neuro-fuzzy inference system
ANN	artificial neural network
AOP	aspect oriented program
BAS	building automation system
BCS	building control systems
BCVTB	building controls virtual test bed
BEO	building energy optimization
BMS	building management systems
BP	back propagation
BF	Bellman–Ford's
BCVTB	building controls virtual test bed
CLIPS	C language integrated production system
CFD	computational fluid dynamics
DP	decision process
DRIVE	distributed responsive infrastructure virtualization environment
DM	dynamic model
EA	evolutionary algorithm
EU	European Union
GA	genetic algorithm
GO	global optimization
GLPK	GNU linear programming kit
LEED	leadership in energy and environmental design
LP	linear programming
LQ	linear quadratic
MAST	multi-agent system technology
MEP	mechanical, electrical and plumbing
MOGA	multi-objective genetic algorithm
MINLP	mixed integer non-linear programming
MIGA	multi-islanded genetic algorithm
MLP	multilayer perceptron neural network
MVGM	multivariate Gaussian model
MDL	minimum description length
MOBS	measured occupancy based setback
MOBO	measured occupancy based optimal
MOGA	multi-objective genetic algorithm
MIGA	multi-islanded genetic algorithm
MOPSO	multi-objective particle swarm optimization
NB	Bayesian network
PD	criteria and periodicity
POBO	predicted occupancy based optimal
PSO	particle swarm optimization
PST	prototype software tool
RSMs	reference semantic models
RSM	reference semantic model
GM	gray models
SVM	support vector machine
SEB	smart energy buildings
SDF	sparse direct factorization
SO	scheduling optimization
SQ	sequential quadratic
SVM	support vector machine
SP	stochastic programming
SA	simulated annealing
SP	stochastic program
UK	United Kingdom
WC	western countries
WSN	wireless sensor network

environment. Some may consider a mix of ailments allied with an individual's work place or residence, etc. called the sick building syndrome (SBS) [8–10]. Therefore, it is necessary to make efforts for the trade-offs between the maintenance of indoor environmental parameters with the reduced energy consumption as a conflicting challenge.

1.3. Current literature survey

A preliminary related search was carried out using the search engines, web of knowledge [11], IEEE explore digital library [12] and Google scholar [13]. The key terms searched in relevancy to buildings include 'energy', 'comfort', 'control' and 'optimization'. Even cited articles were checked and relevant articles were included in the survey. With this broad search, articles were arranged for inclusion in the summary as presented in Table 2. The arrangement has been made in chronologically descending order for presenting a literature survey of the multi-objective optimized control for the energy and comfort management in buildings. This forms the basis for added intelligence for enhancement of control system efficiency in building. However, the major consideration has been given to indoor environmental parameters (thermal, visual, air quality, humidity and plug loads), controllers, occupant's interaction in controls, optimization algorithms and simulation tools.

1.4. Previous literature survey

Various reviews have been already published including [14] reports optimization and sustainable building designs. Dounis et al. [15] have presented advanced control schemes, whereas Nguyen et al. [16] discussed energy intelligent buildings based on occupant's activity, passive design [17], double-skin facades [18] and energy efficient designs [19]. Baos et al. [20] covered the optimization of renewable and sustainable energy, whereas Wang et al. [21] reviewed the field of multi-criteria decision analysis as an aid to sustainable decision-making. In the present review, several features in this area may have coincided and found a lack of systematic reviews of existing research and developments focusing on an intelligent control system for energy and comfort management of buildings, together with an occupant interaction for indoor comfort conditions.

2. Survey trend analysis

According to the collected literature in Table 2, the graphical trend analysis is made in Fig. 2. Several articles have several comfort parameters, algorithms and methods with various control schemes. Therefore, the total number of literature works was not equal in all the part figures of Fig. 2(a)–(i). The notable growth in the area featuring energy and comfort management has been observed in building for over a decade. Energy has been the common objective for our review: whereas other objectives in terms of comfort parameters were thermal at being 48% in the literature, visual 21%, air quality 18%, humidity 6% and plug loads 7% as depicted in Fig. 2(g). The factor of the occupant's preference has been considered at 74% in the literature, and comprised the occupancy pattern, behavior and learning preferences. It has been one-fourth (25%) of the entire survey depicting the cost and tariff considerations, which were mostly considered from the building sector viewpoint; whereas, only a little literature has been

Table 2
Summary of the works that focused on intelligent control of energy and comfort management of SEB's.

Ref.	Year	Country	Journal/ conference	Building sector	Optimization objective(s)							Other objectives	Supply source	Control schemes	Algorithm/ method	Simulation tool
					Energy	Comfort parameters					Tariff/ cost					
						HVAC/ thermal	Artificial lighting	Air quality/ CO_2 concentration	Humidity	Plug loads						
[69]	2013	Greece	Applied Energy	Commercial	√	√	√	–	–	–	√	User requirement and behavior profile	Utility grid	ON/OFF scheduling/ programmed	Scheduling algorithm	Prototype Software Tool
[70]	2013	USA	Industrial & Engineering Chemistry Research	Commercial/ office	√	√	–	√	√	–	√	Pressure and occupancy	Utility grid	MPC control	AMPL modeling	Energy Plus and TRNSYS
[71]	2013	France	Building Simulation	Office	√	√	–	–	–	–	–	Occupants number, architecture, training parameters and inputs of ANN	–	ON/OFF, PID and fuzzy control	ANN modeling	MATLAB/ Labview
[72]	2013	Spain	Energy and Buildings	Office	√	√	–	–	√	–	√	Occupants number, location and culture	Renewable	MPC control	Lagrangian dual method	ANN MATLAB
[73]	2013	Spain	Energy and Buildings	Office	√	√	√	√	–	–	–		Utility grid	MPC control	Predictive control optimization tool	TRNSYS & INSEL
[75]	2013	China	IEEE	Office/ industry	√	√	√	–	–	–	√	User specified time steps	–	–	Ordinal optimization (OO)/GA methods	EnergyPlus
[76]	2013	USA	IEEE	Residential	√	√	–	–	–	–	√	User set value/ feedback and preference	––	MPC control	GA methods	MATLAB Simulink
[77]	2013	USA	IEEE	All	√	–	–	√	–	–	–	Occupant preferences	Utility grid	ON/OFF fuzzy and predictive control	MOPSO	MATLAB
[78]	2013	USA	IEEE	Commercial/ office	√		√				√	User comfort/ specific utility function	Utility grid	Automatic/ illumination/ dimming control	Interior point method (IPM)	MATLAB
[93]	2013	USA	Sustainable Cities and Society	All	√	√	√	√	–	–	–	Occupant preferences	Renewable/ utility grid	MAST	Fuzzy controllers with MOPSO	MATLAB/GUI
[112]	2013	South Korea	International Journal of Innovative Computing Information and Control	All	√	√	√	√	–	–	–	User preference	–	Fuzzy logic	GA/MIGA	MATLAB

[135]	2013	Singapore	Energy and Buildings	Office	√	–	√	–	–	–	–	User occupancy, preference and request	–	Artificial neural network	Constrained non-linear programming	MATLAB Simulink
[136]	2013	USA	Applied Energy	Commercial	√	√	–	√	–	–	–	Occupants occupancy, preference	–	MPC algorithms (MOBS MOBO POBO)/ feedback control	Constrained time step optimization	MATLAB; while IPOPT
[137]	2013	South Africa	Applied Energy	Commercial	√	√	–	–	√	–	–		–	MPC control (quadratic linear programming)	GA weighted summation	MATLAB GA Toolbox
[43]	2012	Denmark	Energy	Residential	√	√	–	–	–	–	√	User behavior and weather conditions	Renewable	–	CPLEX with linear programming (LP) optimization solver	GAMS 20.7
[44]	2012	Iran	Energy	Commercial	√	√	–	√	–	–	√		Distributed generation	–	Standard simplex and branch and bound algorithm	Energy Plus
[45]	2012	Italy	Energy Conversion and Management	Residential	√	√	–	–	–	–	–	Future (user interaction)	Utility grid supply/ renewable	MPC control	Integer programming, linear programming, non-linear programming, stochastic programming, global optimization	LINDO Systems Optimization Software
[46]	2012	Portugal	Energy and Buildings	Commercial	√	√	–	–	–	–	–	Occupants set values	–	Discrete model-based predictive control	MOGA	Radial Basis function ANN
[47]	2012	USA	Energies	Commercial	√	√	√			√	–	Occupants attitude/ satisfaction level	–	Dynamic control	Scheduling optimization	Energy Plus
[48]	2012	USA	Energy and Buildings	All	√	√	–	–	–	–	√		–	–	Support vector regression (meta-model) approach	Energy Plus
[49]	2012	France	Energy and Buildings	Residential/ office	√	√	–	–	–	√	√	Occupants behavior prediction with HMI	Utility grid	Dynamic predictive control scheduling mechanism	Mixed integer linear programming (MILP) algorithm	GNU Linear Programming Kit (GLPK)
[50]	2012	Czech Republic	Energy and Buildings	Office	√	√	–	–	–	–	√	Occupants clothing and activity observed	–	MPC control	General non-linear YALMIP optimization toolbox	TRNSYS and MATLAB
[51]	2012	France	Building and Environment	All	√	√	–	–	–	–	√		–	MPC control	Canonical form of linear programming (LP) method	–

Table 2 (*continued*)

Ref.	Year	Country	Journal/ conference	Building sector	Optimization objective(s)							Other objectives	Supply source	Control schemes	Algorithm/ method	Simulation tool
					Energy	Comfort parameters					Tariff/ cost					
						HVAC/ thermal	Artificial lighting	Air quality/ CO_2 concentration	Humidity	Plug loads						
[52]	2012	USA	Automation in Construction	Office	√	√	–	–	–	–	√	Occupant preferences, and occupant schedules	Renewable/ utility grid	MAST	Markov decision problems (MDP)	OpenGL
[53]	2012	USA	Applied Energy	All	√	√	√	√	–	–	–	Occupant preferences	Renewable/ utility grid	MAST/fuzzy	MOPSO	MATLAB
[54]	2012	USA	Energy Procedia	Office	√	√	–	–	–	√	√		Utility grid	Simulation assisted control	Decision support model scheduling	DOE-2.2
[55]	2012	USA	IEEE	Office	√	√	–	√	–	–	–	Occupant preferences	Utility grid	MAST	MOPSO	MATLAB
[56]	2012	USA	IEEE	Office	√	√	√	√	–	–	–	Occupant preferences	Grid	MAST	MOPSO	MATLAB
[57]	2012	France	IEEE	Residential	√	√	–	–	–	√	–		Utility grid	ON/OFF	Predictive and reactive algorithms	Power-Hardware-In the-Loop (PHIL) test bench
[58]	2012	USA	AACC	All	√	√	–	–	–	–	–		Utility grid	MPC control	–	Energy Plus and BCVTB
[59]	2012	USA	IEEE	Commercial/ office	√	√	–	–	–	–	√	GHG emissions	Renewable/ utility grid	–	CPLEX with linear programming (LP)	General Algebraic Modeling System (GAMS)
[60]	2012	USA	IEEE	Office	√	√		–	–	–	–	Occupants presence and activity	–	MPC control	YALMIP optimization tool	TRNSYS
[61]	2012	Netherland	IEEE	Residential	√	–	√	–	–	√	√	User behavior	Utility grid	ON/OFF	Scheduling algorithm	MATLAB/Simulink
[62]	2012	USA	IEEE	All	√	–	–	√	–	–	–	Occupant preferences	Utility grid	ON/OFF fuzzy and predictive control	MOPSO	MATLAB
[63]	2012	USA	IEEE	All	√	√	√	√	–	–	–	Occupant preferences	Renewable/ utility grid	MAST	MOPSO	MATLAB
[64]	2012	Austria	IEEE	All	√	√	–	–	–	–	–		Renewable/ utility grid	MPC control	-	TRNSYS
[65]	2012	USA	AACC	All	√	√	–	–	–	–	–	Occupants number and preferences	Utility grid	KNITRO non-linear solver	Anytime optimization algorithm	AMPL
[67]	2012	USA	IEEE	Commercial	√	√	–	–	–	–	√	Occupants	Utility grid	MPC control	Sparse direct factorization, Berkeley Library for Optimization Modeling	MATLAB/Simulink
[74]	2012	USA	IEEE	Commercial	√	√	–	–	–	–	√	User defined schedules/ comfort	Utility grid	MAST	AMPL	EnergyPlus
[83]	2012	USA	IEEE	All	√	–	√	–	–	–	–	User set point and occupancy	Utility grid	Central controller	Load shedding distribution and dimming strategy	–

[84]	2012	Turkey	Energy and Buildings	All	√	–	√	–	–	√	√	User choice of comfort, retrofitting strategy replacing regular windows with double-glazed ones,	Renewable/ utility grid	–	Linear programming method	–
[92]	2012	USA	Sustainable Cities and Society	All	√	√	√	√	–	–	–	Occupant preferences	Renewable/ utility grid	MAST	Fuzzy controllers with MOPSO	MATLAB/GUI
[98]	2012	China	Energy and Buildings	Residential	√	√	–	–	√	–	–	Construction cost	–	Contribution ratios	GA simple	CFD
[110]	2012	Taiwan	Energy and Buildings	Office	√	√	–	–	–	–	–		–	–	Hooke–Jeeves/ PSO	EnergyPlus
[111]	2012	Serbia	Energy and Buildings	Residential	√	√	–	–	–	–	–		Utility grid	ANN	GA	EnergyPlus
[117]	2012	Finland	BSO12 Conference	Commercial	√	√	√	–	–	–	√	Design variables investment		Modelica language/ neutral model format	NSGA-II (GA)	DA-ICE/LEED/GenOpt
[118]	2012	Mexico	Energy and Buildings	Residential	√	√	–	–	–	–	√	Number of occupants	Utility grid	–	Sequential search 90 approach	Energyplus/BEOptE+
[120]	2012	Finland	BSO12 Conference	Residential	√	√	–	–	–	–	√	–	Renewable/ utility grid		NSGA-II (GA)	MATLAB/GenOpt
[134]	2012	Netherland	IEEE	Office	√					√	√	Occupancy information	Renewable/ utility smart grid	–	Scheduling Optimization	–
[81]	2011	USA	IEEE	All	√	√	√	√	–	–	–	Occupant preferences	Renewable/ utility grid	MAST	Fuzzy controllers with PSO	MATLAB Simulink
[82]	2011	France	Applied Soft Computing	Commercial	√	√	–	–	–	–	–	–	Renewable/ utility grid	Hybrid PID-fuzzy	Fuzzy reasoning supervision of PID	–
[68]	2011	Italy	IEEE	Residential	√	–	–	–	–	√	√	User preferences	Renewable/ utility grid	ON/OFF scheduling	CPLEX	AMPL
[89]	2011	USA	IEEE	Residential	√	√	–	–	–	√	√	User discomfort level	Utility grid	MPC control	Linear quadratic Gaussian	Stochastic programming formulation
[90]	2011	USA	IEEE	Residential	√	√	–	–	–	√	√	Learning of user preference and comfort needs, CO_2 emissions	Utility grid	–	SVM, MLP and NB	–
[91]	2011	USA	IEEE	All	√	√	√	√	–	–	–	Occupant preferences	Renewable/ utility grid	MAST	Fuzzy controllers with PSO	MATLAB/GUI
[140]	2011	Serbia	Applied Energy	Residential	√	√	–	–	√	–	√	User defined inputs	Renewable/ utility smart grid	Schedule control	–	EnergyPlus
[104]	2011	Korea	Building and Environment	Commercial	√	√	√	√	–	–	–		–	Real time optimal control	Constrained non-linear optimization	LabVIEW
[105]	2011	UK	Building Simulation	Commercial/ office	√	√	√	–	–	–	–		–	Schedule control	MOGA	EnergyPlus/BCVTB
[115]	2011	Belgium		Residential	√	√	–	–	–	–	√	User demand	Utility grid			TRNSYS

Table 2 (*continued*)

Ref.	**Year**	**Country**	**Journal/ conference**	**Building sector**	**Optimization objective(s)**							**Other objectives**	**Supply source**	**Control schemes**	**Algorithm/ method**	**Simulation tool**
					Energy	**Comfort parameters**					**Tariff/ cost**					
						HVAC/ thermal	**Artificial lighting**	**Air quality/ CO_2 concentration**	**Humidity**	**Plug loads**						
			Energy and Buildings											Dynamic control	Dynamic programming	
[121]	2011	India	Energy and Buildings	Office	√	√	√	–	–	–	√	User defined/ input parameter	Utility grid	–	GA	DOE 2.2
[66]	2011	USA	IEEE	Commercial	√	√					√	Occupants comfort and number	Utility grid	MPC control	NLP Ipopt algorithm	
[85]	2011	South Korea	IEEE	All	√	–	–	–	–	√	√	User preference and occupancy, automated metering and control, and owner decisions	–	Scheduling technique	minMax and BatMax Algorithm	Aspect Oriented Programming (AOP)
[133]	2011	USA	Building Simulation Conference	Office	√	√	√	√	√	√	–	Occupancy behavior pattern, motion and acoustics, weather forecast, solar radiation	–	Non-linear MPC control	Newton method from optimization toolbox	MATLAB/Simulink/LabVIEW
[79]	2010	USA	IEEE	All	√	√	√	√	–	–	–	Occupant preferences	–	MAST	Fuzzy controllers	MATLAB Simulink
[80]	2010	USA	IEEE	All	√	√	√	√	–	–	–	Occupant preferences	–	MAST	Fuzzy controllers with PSO	MATLAB Simulink
[122]	2010	Austria	IEEE	Residential	√	√	–	–	–	–	√	User requirement	–	ON/OFF control	ANN	ATplus/Dymola
[127]	2010	USA	ACM Workshop Switzerland	Office	√	√	–	√	–	–	–	Occupancy sensor camera	–	–	Markov chain occupancy model	EnergyPlus
[96]	2009	Switzerland	IBPSA Conference	Residential	√	√	–	–	–	–	–	User input with GUI, construction design	Renewable/ utility grid	Ray tracking	CMA-EA, HDE	CitySim
[97]	2009	Finland	IBPSA Conference	Residential	√	√	–	–	–	–	√	Construction	Utility Grid	MINLP	GA (NASG-II), Omni-optimizer	GenOpt, IDA ICE
[102]	2009	USA	Journal of Building Performance Simulation	Commercial/ office	√	√	–	√	–	–	–	User specify comfort	–	P/PI controller	PSO	Modelica simulation environment/GenOpt/ EnergyPlus
[119]	2009	Finland	IBPSA Conference	All	√	√	–	–	–	–	√	GUI	–	Sequential quadratic programming	PR-GA/GA–RF	MATLAB/IDA ICE 3.0

[125]	2009	Ireland	ACM Workshop USA	Office	√	–	√	–	–	–	–	Consumer preference	–	Occupancy detection control	WSN	LightWiSe
[126]	2009	USA	ACM Workshop USA	Office	√	√	√	√	–	√	–	Occupancy sensor camera	–	Agent based model	MVGM	–
[129]	2009	USA	IBPSA Conference	Commercial	√	√	√	√	√	–	–	Motion detection	–	Semi-Markov model	MDL/PD	EnergyPlus
[130]	2009	USA	IEEE	Office	√	√	√	–	–	–	–	Occupant awareness	–	RSM	–	DRIVE/OSGi
[106]	2008	USA	IBPSA Conference	Residential	√	√	–	–	–	–	–	User needs	–	Schedule control	Sophisticated optimization	Ptolemy II/EnergyPlus/BCVTB/ MATLAB Simulink
[139]	2008	France	Springer	Residential	√	√	√	√	–	√	–	User comfort criteria, behavior and habits	–	MAST	Bellman–Ford's	Java Virtual Machine
[132]	2008	USA	IEEE	Office	√	–	√	–	–	–	–	User satisfaction/ preference	–	Linear programming	Min–Max	Java
[86]	2007	Greece	IEEE	All	√	√	√	√	–	–	√	User preference and dependency	Utility grid	Hierarchal PI-like FLC agents	Gray models (GM)	TRNSYS-MATLAB
[94]	2007	Greece	Building and Environment	All	√	√	√	√	√	–	–	User input/ requirements	–	Fuzzy control	Decision support model	CLIPS
[131]	2007	Germany	Energy and Buildings	Office	√	√	–	√	–	–	–	Occupancy pattern	–	–	Meta-analysis	–
[163]	2007	Greece	Building and Environment	Office	√	√	–	√	–	–	–	User preference and satisfaction level	–	Fuzzy-PD/ON/ OFF controller	Markov decision process	MATLAB Simulink
[88]	2006	France	IFAC Symposium	Residential	√	√	–	–	–	–	–	User habits, outdoor temperature or solar radiations	Renewable/ utility grid	Scheduled dynamic programming	Bellman–Ford's algorithm	–
[109]	2006	Hong Kong	Energy and Buildings	Commercial	√	√	–	–	–	–	–		Utility grid	Dynamic control	Evolutionary programming	TRNSYS
[156]	2006	Slovenia	Solar Energy	–	√	–	√	–	–	–	–		Renewable/ utility grid	Fuzzy PD/PID	Fuzzy rule base	MATLAB
[101]	2005	USA	Energy and Buildings	Office	√	–	√	–	–	–	–	User specified limit, window dimensions, shading	–	Differential algebraic equations	Hooke–Jeeves	GenOpt
[113]	2005	Singapore	Energy and Buildings	All	√	√	–	√	–	Pumps and fans	–		–	ANFIS	GA	MATLAB
[124]	2005	Sweden	Information Sciences	Office	√	√	–	–	–	–	–	Consumer preference	–	MAST		AAP
[128]	2005	USA	ACM Workshop Switzerland	Commercial	√		√	–	–	–	–	Occupancy sensor	–	Decision theoretic formulation	Mobile wireless sensor networks	MICA2 Mote
[149]	2005	Hong Kong	IEEE	–	√	√	–	–	–	–	–	Human supervision	–	ANN controller	Back-propagation algorithm	–
[154]	2005	Switzerland	IEEE		√	√	√	–	–	–	–	Occupancy	Utility grid	MAST		MATLAB

Table 2 (*continued*)

Ref.	Year	Country	Journal/ conference	Building sector	Optimization objective(s)							Other objectives	Supply source	Control schemes	Algorithm/ method	Simulation tool
					Energy	Comfort parameters					Tariff/ cost					
						HVAC/ thermal	Artificial lighting	Air quality/ CO_2 concentration	Humidity	Plug loads						
				Commercial/ office											Fuzzy rule base	
[155]	2005	Slovenia	Building and Environment	–	√	√	√	–	–	–	–		Renewable/ utility grid	Fuzzy PID	Fuzzy rule base	MATLAB
[160]	2005	USA	IEEE	Office	√	√	–	–	–	–	–	Occupant satisfaction	–	Fuzzy logic	frninconi	MATLAB
[142]	2004	Hong Kong	Building and Environment	All	√	√	–	√	–	–	–	Number of occupants	–	PID control	Combined optimal control	TRNSYS
[148]	2004	Italy	Energy and Buildings	office	√	√						–		Fuzzy adaptive PID controller		
[95]	2003	Thailand	IBPSA Conference	Commercial/ office	√	√	√	–	–	–	–	User input set values	–	Scheduling/ dynamic technique	Hill climbing multi-restart; Simulated-annealing; hill climbing with STAGE	SEMPER (Thermal; NODEM and Visual; LUMINA)
[100]	2003	USA	IBPSA Conference	Office	√	√	–	–	–	–	√	User specified limit, window area	–	Adaptive simulation precision control	Hooke–Jeeves	EnergyPlus
[103]	2003	USA	IBPSA Conference	Office	√	√	√	–	–	–	–	User preference	–	Louver system control	FMINCON	MATLAB
[138]	2003	–	Energy	Commercial	√	√	–	√	√	–	–		–	–	–	DOE 2.1
[153]	2003	Greece	Building and Environment	All	√	√	√	√	–	–	–	Occupant pattern		Fuzzy P/PD/ PID/ON/OFF		MATLAB Simulink
[161]	2003	Spain	Applied Intelligence	Office	√	√	√	√	–	–	–	User expectation and demand	–	Fuzzy logic	GA	MATLAB
[87]	2002	Greece	Engineering Applications of Artificial Intelligence	All	√	√	√	√	–	–	–	Occupants' preferences	–	FLC control	Fuzzy optimization through GA	PLC and local operating network
[107]	2002	UK	Energy and Buildings	–	√	√	–	–	–	–	√	Occupant comfort, capital expenditure	Utility grid	–	MOGA	–
[141]	2002	Hong Kong	Energy conversion and Management	All	√	√	–	√	–	–	–	Number of occupants	–	PID control	Dynamic model	TRNSYS
[99]	2001	UK/Brazil	IBPSA Conference	Office	√	√	√	–	–	–	–	Window area	–	Ratios	–	VisualDOE
[108]	2001	UK	IBPSA Conference	All	√	√	–	–	–	–	√		–	Lumped parameter	GA	–
[145]	2001	Switzerland	International Journal of Solar Energy	Commercial/ office	√	√	–	–	–	–	–	User behavior and set points	Renewable/ utility smart grid	Predictive and adaptive PID control	NEUROBAT	ANN/MATLAB

[146]	2001	UK	IEEE	Residential	√	√	√	–	–	–	–	User behavior and preferences	–	Fuzzy/ANFIS	GA-P	–
[150]	2001	Switzerland	Energy and Buildings	Office	√	√	√	–	–	–	–	–	–	Fuzzy/ANN	GA	MATLAB Simulink
[151]	2001	Switzerland	Building and Environment	Office	√	–	√	–	–	–	–	User wishes	–	Fuzzy	GA	MATLAB
[152]	2001	Greece	Energy and Buildings	All	√	√	√	√	√					Fuzzy PD/ON/OFF	–	MATLAB Simulink
[143]	2000	Hong Kong	Building and Environment	All	√	√	–	√	√	–	–	Occupant acceptable comfort	–	PID control	GA	TRNSYS
[144]	2000	Belgium	Solar Energy	Commercial	√	√	–	–	–	–	√	User behavior, point of view and habits, forecasting and building behavior	–	PID control	Linear quadratic programming	Matlab Optimisation Toolbox/ TRNSYS
[147]	2000	Greece	Applied Energy	Residential	√	√	–	√	√	–	–	User behavior and preferences	–	Fuzzy control	Runge–Kutta method	Turbo C
[116]	1999	Finland	Energy and Buildings	Residential/ office	√	√	√	–	–	–	√	User preference and behavior, window area, insulation thickness	Renewable/ utility grid	–	Hooke and Jeeves	Optimization tool design
[158]	1999	Japan	IEEE	Office	√	√	–	–	–	–	–	User preference and occupancy	–	Fuzzy control	ANN comfort learning	MATLAB
[123]	1998	USA	AAAI Conference	Residential	√	√	√	√	–	√	–	Occupancy considera-tion	–	Adaptive control	Back propagation ANN	–
[157]	1998	Canada	IEEE	Residential	√	√	–	–	√	–	–	Occupancy		Fuzzy control	Fuzzy rule base	TRNSYS-MATLAB
[114]	1997	Hong Kong	Energy and Buildings	–	√	√	–	–	–	–	–	Overshoot, settling time, and mean squared error	–	PID controller	GA	HVACSIM +
[159]	1997	Hong Kong	Energy and Buildings	–	√	√	–	–	–	–	–		–	PI controller	GA	SIM +
[162]	1995	Hong Kong	Building Simulation	–	√	√	–	–	–	–	–		–	Optimal control rule	GA	–

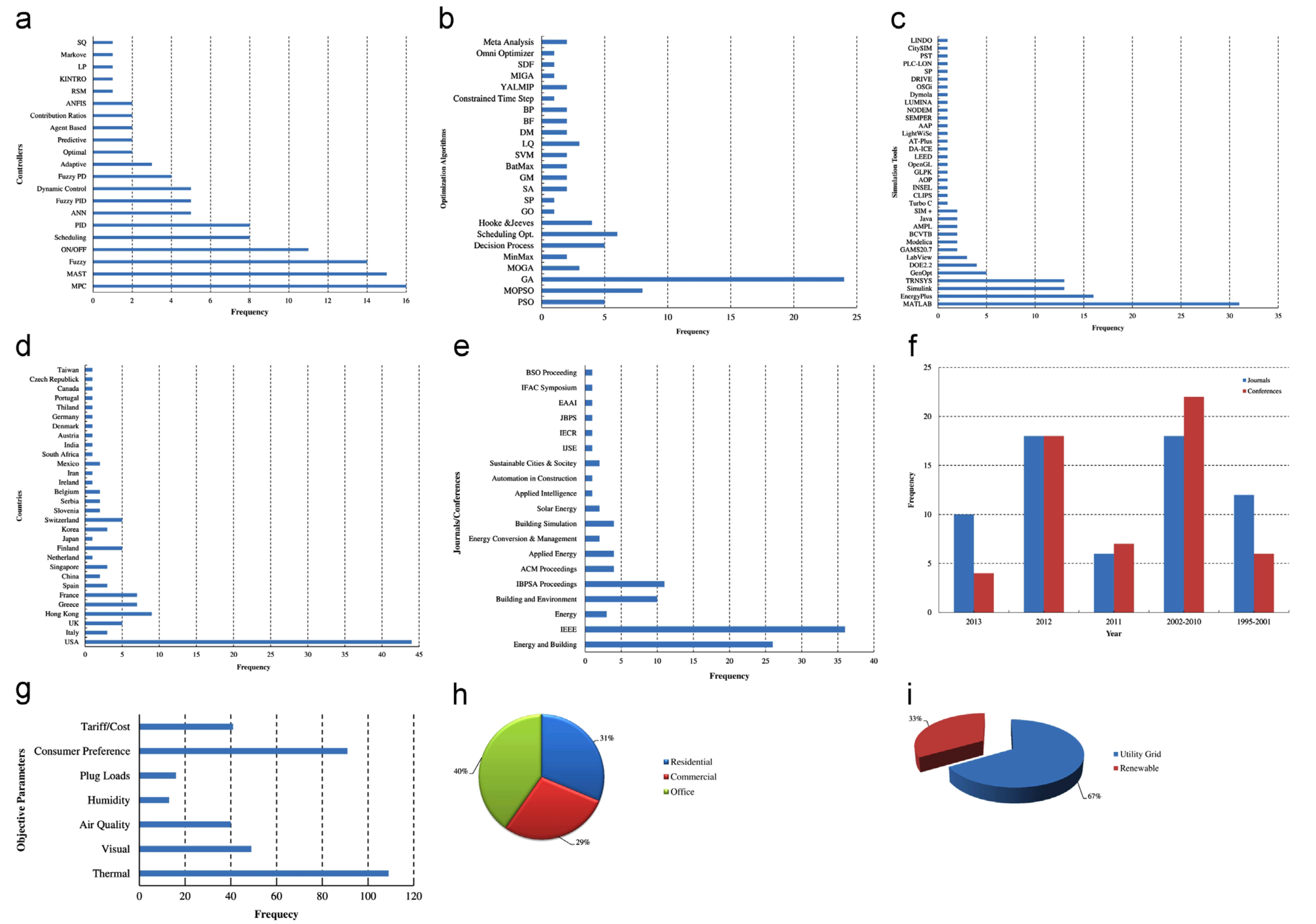


Fig. 2. Summary of the compiled research work from Table 2. (a) Controller trends. (b) Optimization algorithm trends. (c). Simulation tool trends. (d) Trends of survey countries. (e) Publications. (f) Publications timeline. (g) Comfort objective parameter trends. (h) Building type trends. (i) Building supply source trends.

considered from the utility grid. The major control systems employed were MPC that was found at 15% in literature, MAST constituted 14%, Fuzzy was at 13% and ON/OFF controls were at 10%. This is presented in Fig. 2(a). However, other controllers, like adaptive, predictive, and optimal control strategies, have become obsolete. The agent based and contribution ratio controllers are getting more popular among researchers due to their particular assigned task capabilities. The algorithms, which have mostly been employed in the literature for optimization, are GA—29%; MOPSO—10%; and scheduling optimization—6% as shown in Fig. 2(b). The distribution process and MOGA are getting the attention of researchers; they are almost at the same percent in the survey. Whereas tools used for the simulation of control systems with an optimization algorithm are MATLAB—26%, energy plus—13%, and Simulink and TRNSYS are at 11% each as depicted in Fig. 2(c).

The countries working and publishing there research is shown in Fig. 2(d), USA seems to be very keen for its building energy efficiency. Whereas other countries are yet, may be, unable to identify the potential of energy savings with this sector. Most of the European countries like Switzerland, Finland, France, Greece and UK show some interests in considering rising energy demand of building sector. However, Singapore being the largest consumer of building energy strives its research focus on the area. Fig. 2(e) shows the publications with journals and conferences, which focuses the researchers interests are targeted research objectives with buildings. However, Fig. 2(f) depicts the publication timeline for the referred journals and conferences according to the scope of the literature survey.

The building sectors encountered in the literature survey constituted 40% of the buildings, 31% residential and 29% of the commercial buildings Fig. 2(h). The energy supply source is an important element for the sustainability of a building, which has also been observed in our survey. The utility grid supply has been large as it comprised 67% of the literature; whereas the trend regarding the renewable sources constituted 33% (Fig. 2(i)). The renewable energy sources generally employed in buildings are photovoltaic, wind turbines, biomass and hybrid systems of these resources.

3. Control systems in buildings

The building control system (BCS), also termed building automation system (BAS) or building management system (BMS), has in no doubt led to the general specifications of building monitoring and metering systems. These control systems are generally centralized, integrated, hardware and software networks; thus, they monitor and control the indoor climatic conditions in building facilities. The operational performance of the buildings along with the safety and comfort of the occupants is normally ensured with these control systems.

Building controls are normally instigated with mechanical, electrical and plumbing (MEP) system controls. For instance, regulation of building environment is a multivariate issue, possessing solutions, which are not unique due to occupant's legitimacy. However, the aims of the building management system for energy

and comfort are (i) comfort requirements in achieving a high comfort index (for thermal, visual, air quality, humidity and various plug loads). In addition, the occupant's preferences, their behavior, occupancy pattern and adaptive comfort needs. (ii) Integration of the building comfort conditions with energy and cost saving strategies. For the fulfillment of the comfort requirement demand controls, the actuators are employed. Such as for heating ventilation and air conditioning (HVAC) systems for thermal comfort which includes control of its various parts: chillers, boilers, air handling units (AHUs), rooftop units (RTUs), fan coil units (FCUs), heat pump units (HPUs), variable air volume boxes (VAVs), etc. Visual comfort involves artificial lighting technologies, demining control, solar radiation blind control, etc. Air quality has been treated with window openings, air conditioning units, and fan regulators. Humidity comfort employs dehumidifiers, desiccant flow rates and certain humidifiers, etc. Plug loads constitute kitchen appliances, laundry accessories, charging portables, etc.

Various building control schemes for indoor environments can roughly be categorized as conventional controllers and intelligent controllers.

3.1. Conventional controllers

Building control systems are basic entities in building energy management for attaining energy efficiency and sustainability. Various standard control schemes, such as an on/off switching controller, i.e., thermostats, proportional–integral (PI) and proportional–integral–derivative (PID), have been extensively used in building engineering [164–168].The on/off controllers have been primarily used for indoor temperature regulation. However, energy consumption and wastage are usually huge due to the substantial instabilities and frequent overshoot of the set points. These control systems have been employed in various applications and disturbed environmental conditions, and have been poorly performing and generally have not been offered optimal control strategy.

Generally, P, PI and PID controllers are closed loop/feedback controls, not having any direct knowledge of the system to be controlled, and they possess constant parameters. They provide poor control performance for noisy and non-linear processes having large time delays when used alone [169–172]. By the cascading of multiple PID controllers or linking feedback and feed-forward controllers, the control performance of these schemes can be enhanced [174]. Whereas the considered system knowledge can be fed forward and integrated with the PID output for the overall system performance enhancement. However, these control systems have improved the controlling scheme but the improper gains' selection made the entire system unstable. Thus, control designers and engineers turned to optimal, predictive and adaptive techniques.

The above control strategies did not consider the comfort factor but were only concerned with energy consumption savings. Ensuring thermal comfort and limiting set-point overshoots with energy savings, significant research was carried out in the 1980s on predictive [174,175], adaptive [176,179] and optimal [173,147] controllers. Due to various complications and implementation challenges, there has been no industrial development followed with these schemes. Since these are model-based control schemes, they require a model for building control strategy. However, each building possesses ambiguous non-linear thermal behavior related to its structure, construction material, location, usage and climatic conditions [177,178].

The capability of the self-regulation and adaption of the environmental conditions in numerous buildings has been provided by adaptive controllers [124]. This inherently non-linear dynamic system estimates uncertain control parameters using measured system signals. These control systems try to maintain a constant performance in the occurrence of uncertainty and continuous variations of the control parameters. Very few researchers have employed adaptive techniques that are able to learn a building's characteristics and its environmental state [180]. Whereas predictive controllers take into account a model for impending disturbances, such as occupancy information, solar radiations, etc. These controls improve thermal comfort through the overheat reduction from night cooling [181–183]. Non-linear model predictive control may simply switch to altered operational modes, say when an HVAC system fails, and may deal with state space dimensional models. Dynamic programming also has advantages in that it deals with weather uncertainty and all the calculations are made off-line [173]. This significantly enables the actual installation of the controller. However, almost negligible onsite computer power is needed and it poses less starting problems if power breakdown occurs. However, this makes it difficult to build a control algorithm taking weather effects explicitly into account. Dynamic programming is one of the few optimal control algorithms, which considers weather effects, explicitly.

Since the above control solutions may not always be feasible and suffer from various limitations, these schemes require a model of the building. The use of control elements complicates the cost minimization function. Inaccurate results may be obtained due to the sensitivity of the controllers in a real time application. Yet these techniques only work with energy savings and wastage; whereas the problem of the comfort index has yet to be addressed. These control systems may not be user friendly, as the occupants are not able to participate in the configuration scheme.

3.2. Intelligent controllers

Various researches were focused on in the 1990s. The main research trends in the field of advance energy and comfort management controls were emerged. (i) Learning based methods including artificial intelligence, fuzzy systems and neural networks—fuzzy with conventional controls, adaptive fuzzy neural network (ANFIS) systems, etc.; (ii) the model based predictive control (MPC) technique, which follows the principles of the classical controls; and (iii) agent based control systems.

3.2.1. Learning methods

Various learning controls have been developed and successfully applied to electrical and mechanical systems, mostly in robotics, automation and manufacturing areas. These controls have been designed for attaining system stability and performance through the strange and unknown learning possibilities, which exist in system dynamics. These controls are designed like artificial intelligence having fewer requirements of the detailed models.

Fuzzy logic controllers using the rule base would allow the application of a multi-criteria control strategy incorporating an expert system. The implementation of the complex control techniques, fuzzy controllers, should operate rationally and offer enhanced performance. However, fuzzy systems are able to map the non-linear model characteristics of the system performance. In this scenario, fuzzy adaptive controllers have been admirably applied to heating systems [184] with the objective to capitalize on energy efficiency, thermal comfort, visual comfort [185] and natural ventilation [186].

The hybridization of PID and fuzzy controllers has also been proposed in a parallel structure and the fuzzy supervision of the PID control system. The integration of the two control strategies offers the advantage of both schemes, thus allowing the fulfillment of what is lacking in each control system. Various methods exist to

employ fuzzy logic in closed loop control [187]. Therefore, dealing with the usage of both schemes employs control process's measured signals as inputs and outputs of the fuzzy system for driving the actuators. These controllers are mainly model dependent and need prior human knowledge of the control system for the range of proportional gain. In addition, they can adapt to varying environments. In the fuzzy controller output requirement, one may employ fuzzy P, PI or PD hybrid controllers. A fuzzy PI controller is generally considered as an incremental controller; it computes a control increment of both the error increment and the output. In combination with an inference mechanism, it is used off-line for the generation of look-up numerical tables. Integral and proportional PI controllers have been pooled for advantages to offset the removal capability and control stability, respectively. Whereas the fuzzy PD controller calculates the control signal values from both the error increment and the output. This controller has a limited capability with abrupt load variations and noise measurements.

Similarly, an artificial neural network (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) have been used as control tools [188] for environmental parameter prediction. It includes indoor illumination, temperature and relative humidity [189] and has been used for the inhabitant's behavior modeling related to energy use [190].

3.2.2. Model-based predictive control method

These controllers' popularity has grown among researchers and industry in various engineering fields during the last decade. In building system controls, MPC provides worthy prospects for the pursuance of energy efficient control, system dynamics, and stiffness along with time delays. However, it does not have any attention due to its significant computational requirements. It is able to deal with constraints on input/output signals in multi-input and multi-output (MIMO) systems. This is mainly significant for thermal control in buildings because it allows the maximum potential of the commands in order to impose temperature bounds. It also includes instabilities in the optimization process directly; thereby, aiding indoor weather forecast. The nurturing of the computational technology has raised MPC in this field due to its advantages over other control methods. Since it involves information of dynamic modeling and occupancy predictions in contrast to rule-based control systems, it leads to even more energy savings.

It has been shown in a variety of simulation-based research that MPC can be adapted for building system controls like cooling [191], ventilation [192], water heating [193] and floor heating [194]. Therefore, simulation studies have confirmed that MPC has outperformed other control schemes. However, it offers a huge amount of energy efficiency without compromising the indoor building comfort conditions [195]. The hypothetical researches on MPC investigated with real buildings [144] have reported the satisfactory performance of MPC in reducing energy consumption and enhancing thermal comfort.

The adequate control scheme of MPC in building thermal control projects includes UC Merced Campus in the USA [191], Opti-Control in Switzerland [195], and 'MIGRER' in France [196]. Except for control technology, MPC has found its applications in various areas of building research. It provides peak demand reduction in irregular heating [197] and cooling [198] or even the estimation of heating loads [196]. It can also compute the minimization of the cost function for future time horizons. Some of the MPC advantages are discussed as presented below:

(a) MPC takes into account disturbance predictions (that are occupancy profiles, weather, etc.) in trying to regulate, appropriately, the control activities along with the convex optimization strategy [199].
(b) It usefully exploits the building's thermal mass compared to the conventional controls (such as PID, weather compensated or rule-based control) [200].
(c) It is able to take account of the energy price variation and can be easily employed in the optimization problem formulation [204].
(d) Shifting and minimization of the energy peak loads can be handled within a definite period due to the selection of the tariff and least operational cost [201].
(e) Optimization can be carried out from a pool of predefined signals and it can select the appropriate signal [191].
(f) The distributed control strategy can also be formulated; thus, the computational load has been split among various solvers [202].

However, the MPC has the potential of reduction in the energy and cost functions along with the optimization domain, which has as yet not been explored entirely. Various studies have considered specific machines and variables; those are chillers, air handling units, humidity, air quality, etc. But, an integrated building control is still lacking. Since there is apparently high risk in the potential of energy and cost savings of the advanced automated techniques, this impedes smart grid initiatives and market penetration. MPC technology involves huge costs for modeling, data collection, expert monitoring and deployment; due to which, it is not worth-it for medium sized buildings. Therefore, narrowing down the system cost and complexity is essential to determine a minimized optimization domain and a critical degree of freedom. It is also significant for various electricity market incentives and programs, such as day-ahead bidding, real-time pricing, and demand response impacts on the costs of MPC over existing control architectures.

3.2.3. Agent based control systems

In artificial intelligence, the best control results can be obtained when sensible action is applied, which can be achieved with individual rational agents. Agents are generally virtual or physical entities that co-operate rationally in an environment with both perceiving and affecting qualities. Moreover, these agents are capable of coordinating and communicating with each other and with their environment, too. Agents in a control system are arranged in multiple layers according to their functionality. However, these agents possess a distinctive behavior but share and co-operate some of the common properties. The framework of multiple agents may be employed to model complex problems with several cyber agents in simulations or physical agents with proxies, which may act in the real world.

The design of multi-agent system technology (MAST) requires the splitting of a huge complex problem into several sub-problems, which can be dealt with by their representative agents. Therefore, the resolution of sub-problems is integrated to change the current global state over agent–agent coordination [203]. This system comprises various distinct functionalities, such as evaluative, speculative and educate. Therefore, it allows operators and policy makers to understand the system's working capabilities, make possible changes to identification through emerging theories and obtain information on decisions from future system designers [204].

The building intelligent control with a MAST framework allows the learning of building occupancy trends and energy resource coordination as well as the ability to respond to real time indoor environmental conditions. Identifying the potential of the distributed scheme of building energy optimization, various researches

have employed MAST technology to manage reactive and anticipatory control of the HVAC systems, and lighting and air quality for smart homes [205] and office buildings [127]. It has been used to coordinate the building of electrical devices and heating to optimize smart grid energy demands [206]. It has also been employed for the management of micro grids and renewable energy in building supply systems in coordination with the utility grid supply [207] along with energy tariffs and trade-offs for renewable energy supplies [116].

The MAST system integrates facility systems and appliances with the sensors and actuators. These controllers in energy management systems work to satisfy and find balances between the building energy requirements and the occupant's comfort [122]. Conflict resolution of multiple user preferences in buildings [208] and the complexity of an optimal building environment control have been addressed [209]. The thermal response of buildings with respect to the outdoor climate as well as the occupancy loads for the management of building energy and comfort management has been studied [210]. Occupancy prediction and behavioral characteristics in zone and room levels and the peer influence of simulations have been performed and developed using the MAST occupant simulation tool [211].

The MAST approach has been used to manage services that can only be modeled by non-linear equations [212]. This technique provides an open architecture where agents can be configured easily and dynamically. It provides a new agent's compatibility during run time without interruption of a system's normal operation. These systems are imitated with a number of various rules/constraints, which can be programmed into the agents. The agents in the MAST system must be able to display an adjustable autonomy and provide manual override where human and artificial agents may act simultaneously [213].

4. Computational optimization methods

Various engineering, science and industry applications involve ubiquitous simulations, certain modeling, data analysis and computational optimizations. These aspects with the limited resources of time and money lead, consequently, to the optimization practice. Engineers and researchers continuously try to optimize systems, whether to minimize cost and energy consumption or alternatively, to maximize output, efficiency, profit and performance. Modeling, computation and search algorithms are the integrated components of an optimization process.

An optimization problem can be formulated in numerous ways; by far most broadly, the formulation of the optimization problem is non-linear as shown below:

$$\text{Minimize,} \quad f_i(x) \quad (i = 1, 2, \ldots M) \tag{1}$$

Subject to the bound constraints

$$h_j(x) \quad (j = 1, 2, \ldots, J), \tag{2}$$

$$g_k(x) \le 0 \quad (k = 1, 2, \ldots, K), \tag{3}$$

whereas f_i, h_j and g_k are non-linear functions in general. The design vector $x = (x_1, x_2, \ldots x_n)$ can be discrete, continuous or mixed in an n-dimensional space. The function f_i is the cost or objective function and if $M > 1$, the optimization would be multi-criteria or multi-objective. Whereas $h_j(x)$ and $g_k(x)$ are equality and inequality constraints.

Yet in building applications, optimization studies employ a single objective and constitute almost 60% of the studies; this means that in an optimization run, only one cost function can be optimized [14]. Nevertheless, building energy research deals with conflicting issues for optimization [120,163], such as the minimum energy consumption vs. the maximum comfort (i.e., thermal, visual, air quality, humidity, plug loads, etc., may include individually or in combination) and vs. the tariff costs, vs. renewable energy trade-offs, etc. Therefore, a multi-objective approach seems more relevant than a single objective. Various methods have been proposed to solve multi-objective problems; however, the scalarization is the simplest over others. In this, each cost function is assigned a weight factor and is simplified through the criteria of the weighted summation [137]. Thus, it transforms the multi-objective into a single objective problem with the help of linear scalarization as depicted in the following equation:

$$\min_{x \epsilon X} \sum_{i=1}^{n} w_i f_i(x) \tag{4}$$

whereas w_i is the weight factor of the ith objective function ($w_i > 0$).

Generally, objective functions are equally significant and probably in conflict. In addition, usually, no single optimal solution is common for all the objectives. Therefore, multi-objective optimization looks for trade-offs, rather than a single solution. Multi-objective optimization includes (a) the search for the Pareto optimality set of non-dominated solutions with negotiations among different objectives and (b) the selection and evaluation of the respective solutions based on further information availability, prioritization, cost opportunity, satisfactions, etc.

Although various optimization techniques have been established and reviewed [214,227], the genetic algorithm (GA) is the most recognized technique in building performance analysis. Dalamagkidis et al. [163] utilized the detached dwelling optimization of 3-phase GA; whilst Griego et al. [118] employed the GA method for energy and thermal comfort with feedback control including occupant preference. Singhvi et al. and Guillemin et al. [128,150] employed ANN training and validation, and coupled it with GA for the optimization of thermal comfort and energy consumption. Huang et al. [98] used GA with a contribution ratio of each optimization parameter of energy, thermal and humidity levels; whereas [87] employed GA for fuzzy optimization to balance energy and comfort, which included air quality, illumination and thermal factors.

The multi-objective genetic algorithm (MOGA) has been used with schedule control and discrete predictive models [90,147,149] for the trade-offs between energy and thermal and illumination comfort conditions. Safdar and DoHyeun [112] utilized the multi-islanded property of GA (MIGA) for energy and the comfort index. The exceptional feature was that the population had been divided into sub-populations and thus genetic operators were independently executed on this sub-population. This depicts quite a slow recovery issue in comparison to GA. However, the energy consumption is quite less or may be equal to the GA technique, NSGA-II, in optimizing energy consumption vs. visual and thermal comforts [99,123]. Being population-based methods, GAs are well suited to solve multi-objective optimization problems. The performance has been evaluated for three multi-criteria algorithms [123], which were NSGA-II, aNSGA-II and pNSGAII, based on the building optimization and two benchmark test problems. This supported NSGA-II for its high-quality true trade-off solutions with very few evaluation runs and it attained better convergence.

Various other strategies have included the Multi-objective Particle Swarm Optimization (MOPSO) in optimizing thermal, illumination and air quality comfort and building energy consumption [91–93] and have also provided the opportunity for occupant preferences. Hooke–Jeeves [110,116] utilized an algorithm for optimal solutions among energy and comfort in low energy buildings. A comparison of the Hooke–Jeeves algorithm with the GA, PSO, Coordinate search algorithm, Hybrid PSO-HJ algorithm, Simplex algorithm of Mead and Nelder, Discrete Armijo

gradient algorithm and PSO mesh search for the optimization of energy consumption in buildings has been performed in [100,101]. It has been found that GA outperformed in all comparisons and as close to the best minimum, consistently; however, the HJ algorithm was trapped at the local minimum. The hybrid HJ-PSO attained the overall best cost decrement though only after a lot of simulation runs. Consequently, the other algorithms' performances were not satisfactory and were found to be unstable. Further, the implementation of the simplex algorithm and Discrete Armijo gradient algorithm has not been suggested for building optimization problems.

Linear programming optimal solutions ought to occur on the exterior point when each function and constraint is linear [43,51]. Non-linear programming allows a range of non-linear objective functions and constraints [50,78,106]. Differential evolution [215] and hill climbing [97] algorithm values of the variables are perturbed with introducing modules of other solutions to enhance the performance index in the optimization strategy. Whereas evolutionary programming (EP) [109] and genetic programming (GP) [216] provide a hierarchical representation of the variables that have been allowed by the tree-structure. In general, variable values are altered in EP and GP; whereas the tree structure also varies along with the variables. Bellman–Ford's algorithm [88,139] and optimal search min–max algorithm [87,135] have been employed for the optimization strategy of the energy and thermal comfort levels utilizing scheduling schemes. In simulated annealing [95], solutions have been perturbed far from their previous positions and retained the probability for better solutions that steadily enhanced with time.

Other strategies for optimization in the literature are the anytime optimization (AO) [108], ordinal optimization (OO) [117], femicon [103,163] and meta-analysis [134]. It has been generally perceived from these studies that the utilized methods have aimed at making a Pareto optimal representative subset from which an appropriate solution can be driven by the decision-makers of the selected problem.

5. Simulation tools

Due to the diverse complexity and heterogeneity of the control schemes and optimization algorithms in smart energy buildings (SEBs) as well as the vigorous interaction and needs of the occupants, cost functions, accuracy and time constant, there should have been a clear strategy for the affordable and easy to use simulation tool. With the development of control systems, researchers have tried to negotiate between the conflicting challenges in buildings. This has let the researchers to have a certain simulation platform to evaluate and analyze control system optimization strategies. There are various simulation tools available with the US Department of Energy (DOE) in the building energy software tools' directory, which can be accessed from [217].

Building simulation programs were traditionally written with imperative languages that are FORTRAN (FORmula TRANslation), which is primarily suited to scientific and numeric computations, and C and C++ [150], which generally facilitate structured programming capabilities. They employ various iterative algorithms including the Runga–Kutta method, Newton Raphson, etc. However, traditional programming languages allow further development in new versions of software for ease of use; these comprise ESP-r, DOE-2 and Energy Plus [104]. A program developer composes a sequence of instructions, which assign values in a predefined order of execution of variables. These platforms typically write amalgamated codes; thus, they determine the physical processes for the resolution of a numerical problem and data management [104].

However, at present there have been some packages, which offer a platform for multi-criteria optimization. The MATLAB [218] optimization toolbox contains the MOGA algorithm, Min–Max, FMINCON, artificial neural network (ANN), fuzzy inference system (FIS) and Simulink toolbox. Fuzzy inference systems with various conventional controllers have been widely employed in SEBs as discussed in the above section. ANNs have also been widely employed for environmental and building performance predictions. ANN prediction models of indoor building environmental discomfort and energy consumption have the potential for control setting optimization in an on-line method [73]. The prime goal of replacing models with ANNs reduces efforts for physical model development, regulation and validation. Building simulations can also be carried out with the HYBCELL numerical model comprising coupled models, thermal models and pressure airflow models [219]. This tool has been developed in the MATLAB/SIMULINK environment and is an open source. This can be coupled with controllers, such as ON/OFF, PID and fuzzy, and can be optimized easily within the same platform.

TRNSYS (a Transient System Simulation Program) [220] has been utilized for the dynamic simulations for cooling-down and heating-up thermal building zones and control systems [68]. This tool allows researchers and scientists to save effort in the building model's creation and replicates time constants through existing building data. Magnier and Haghighat [47,153] used TRNSYS simulations for the training of an ANN and coupled the trained and validated ANN with the GA for the optimization of energy consumption and thermal comfort index. This was performed due to the decreased time for the generation of a database; otherwise, TRNSYS and GA direct coupling could have taken 10 years instead of 3 weeks. However, the simulation time was very small.

The Energy Plus simulation package is a stand-alone module and does not possess a 'user friendly' graphical interface. Integration of the optimizing algorithm into the Energy Plus package for the reduction of the occupants' effort for coupling between this tool and the optimal algorithm has been proposed [221]. Direct search family optimization algorithms were integrated, which greatly limited the search performance. Automated coupling of this engine with formal optimization techniques with an impartial data standard have been used with the Ar-DOT program for seamless integration [222]. The support vector machine (SVM) technique has also been employed for producing various meta-models for the Energy Plus building models [49]. A sensitivity analysis has been performed for selecting the most influential variables for further optimization. This resulted in equivalent optimized solutions with both meta-models and Energy Plus.

Other complex building emulators have included electrical consumption, which can be programmed in the object oriented modeling language Modelica, with Dymola being a software package, which supports the Modelica modeling language. Dymola software has been generally employed for the object-oriented modeling of complex systems [125]. It has been utilized in various domains (e.g., electronics, physics, etc.). ATplus, another general purpose commercial simulation software designed to simulate building thermal models dynamically, comprises thermal storage and heat flow balances. In [125], these simulation engines constitute the predefined HVAC components and various control schemes for heating systems, i.e., discrete, continuous and fuzzy controllers. It allows coupling of weather models into computations, such as weather relative influences, solar radiation, etc.

BEopt [223] and Op-E-Plus [224] offer multi-criteria platforms, explore vast parameter space and search for economically effective energy conservation solutions. The two engines exploit DOE-2 and/or Energy Plus and a sequential search method for the simulation and optimization, respectively. These computational programs possess user-friendly interfaces and are fully functional

simulation–optimization search platforms, which can be employed for building design practice. The zero energy building design support tool (ZEBO) facilitates the benefits of building performance simulations for early design stages of projects in hot and humid environments [225]. Thus, an added contribution for the integrated building simulation and optimization method resolved a barrier. The SIMBAD (SIMulator for Buildings and Devices) environment [209] allows various plug loads for the simulation and optimization purposes. However, very little attention has been given to real time building simulations, which allow for physical devices and real conditions [226]. This has been provided for through the Power Hardware-in-the-loop (PHIL) for the SEB's testing and validation.

An ACHE system aims for energy conservation and personal comfort [127]. It learns the personal preferences through the behavior of the persons inside the buildings. However, the ACHE system is unable to identify and locate occupancy; therefore, it is unable to deal properly with the occupants' preferences. It develops a surrogate optimization method with the application of polynomial regression to the computational fluid dynamic (CFD) simulation output. This is in order to derive explicit cost functions thus optimizing them by employing a simple deterministic method. Dynamic simulations are also performed with HVACSIM+ [59,60,117]. They simulate any system of discrete components and are determined with a set of non-linear ordinary differential and algebraic equations. Another generic multi-parameter optimization engine for building system optimizations is GenOpt (Generic Optimization Program) [120].The prime goal of this optimization tool is to determine the best values of the design parameters within no time. Cost function optimization is generally evaluated with external simulation engines such as Energy Plus, TRNSYS, IDA-ICE, DOE-2, or Dymola. Thus, they are developed where cost function derivatives are not available/exist and are computationally exclusive. AMPL is also an influential modeling language for optimization problems of both linear and non-linear cost functions [76]. It is not capable of solving optimization directly; however, it requires solvers, such as KNITRO, LANCELOT, SNOPT, MINOS, IPOPT, CPLEX, etc. AMPL is a global solver; therefore, it is not concerned about reaching the local extreme point.

6. Conclusion

6.1. Major survey findings

Generally, global building energy demand is at 40% and will soon touch 60% according to the statistics [228]. Buildings, old or new, private or public, residential, commercial or office, and single to multiple occupants, are where individuals live, work and play. Thus, buildings make up the city's landscape and are better shelter to the people. Therefore, cities need to make their buildings intelligent, smarter, more energy efficient, green and livable.

This review draws attention to the investigators, experts and researchers for the building cost function optimization and control of energy and comfort management in SEBs. At present, it confirms that most of the developed and the developing countries are taking interest in smart building energy efficiency and indoor environmental comfort. There has been an increasing trend for automated control systems and the computational optimization strategies. Moreover, various intelligent techniques have been added in the control system frameworks with numerous computational algorithms in order to enhance the efficiency of the building control schemes. Various control schemes proposes the promising strategy but yet agent based, adaptive neuro-fuzzy inference systems, and other techniques need to be explored comprehensively. Along with this, optimization algorithms such as multi-objective genetic algorithm, simulated annealing, meta-analysis and others also require in depth exploration. In terms of simulation tools, more or less they may have impact on simulation strategies, which need to be exploited and explored for standardization and commercialization. The implementation of the intelligent systems can save a significant amount of energy and wastage and CO_2 emissions. In addition, the realization of these systems, building occupants' behavior, activities and preferences are the most important feedbacks for smooth building automation.

The supply sources for the building energy and indoor comfort requirements are open ends for trade-offs. Whereas the integration of renewable micro-grid resources and utility grid supply in buildings needs more research effort. Various terms and conditions need to be negotiated and optimized, including power supply directional flow, TOU tariff variations, quality of supply, consumer preferred supply requirements etc.

This turns buildings with a huge amount of sensor data and enhanced computational support for the building energy and comfort systems to be complex. Along with this, data management in building control systems is turning out to be a gigantic challenge for the near future. Nonetheless, great progress in the computer science field and ICT technologies has been in demand for effective multiple computational tasks and communication/coordination including with devices and occupants. Even the policy makers must stick to certain standardized indoor comfort set points, renewable generating sets for particular power supply sources, certain control systems and optimization algorithm performance evaluations.

6.2. Future perspectives

- The applicability of current systems still needs research efforts with intelligent reasoning and coordination to deal with the dynamic input and distributed controls.
- Occupants' attitudes and preferences pose significant impact on the usage of energy resources and consequently, the optimization of building energy and comfort management is yet an open challenge for real time interface and computational support.
- An important future development of the research must constitute quantification of the effective energy savings and evaluation of the impact on the occupants' satisfaction.
- More importantly, certain adaptive and predictive systems should be developed for forecasting the energy demands and occupants' comfort demands, behavior occupancy time expectancy, etc.
- Various other artificial intelligent techniques, such as fish swarm algorithms, Type-2 fuzzy set modeling, differential evolution and various hybrid techniques, etc. need to be future research objectives.
- Keeping in view the smart appliances, integration of safety, security and monitoring should be an option for future technologies.
- Development and management of databases for energy, occupants and comfort parameters inside buildings should be properly dealt with and data collection should be sufficient and precise under various conditions for further research and analysis.

Acknowledgment

The authors are thankful to the Universiti Teknologi PETRONAS for the financial support and motivation to conduct research.

References

[1] International Energy Agency. International Organization for Standardization (IEA–ISO). International standards to develop and promote energy efficiency and renewable energy sources. Special ISO focus—world energy congress; 2007. p. 5–10.

[2] Communication from the Commission to the European Parliament, The Council, The European Economic and Social Committee and the Committee of the Regions; 2010.
[3] Dixon R, McGowan E, Onysko G, Scheer R. US energy conservation and efficiency policies: challenges and opportunities. Energy Policy 2010.
[4] WBCSD, transforming the market: energy efficiency in buildings, survey report. The World Business Council for Sustainable Development; April 2009.
[5] Shaikh PH, Mohd. Nor NB, Nallagownden P, Elamvazuthi I, Ibrahim T. Robust stochastic control model for energy and comfort management of buildings. Australian J. Basic Appl. Sci. 2013;7(10):137–44.
[6] Shaikh PH, Mohd.Nor NB, Nallagownden P, Elamvazuthi I. Building energy management through a distributed fuzzy inference system. Int J Eng Technol (IJET) 2013;5(4):3236–42.
[7] Levermore GJ. Building energy management systems: applications to low-energy HVAC and natural ventilation control. 2nd ed.. London: E & FN Spon; 2000.
[8] Gupta S, Khare M, Goyal R. Sick building syndrome—a case study in a multistory centrally air-conditioned building in the Delhi City. Build Environ 2007;42(8):2797–809.
[9] Wang BL, Takigawa T, Yamasaki Y, Sakano N, Wang DH, Ogino K. Symptom definition for SBS (sick building syndrome) in residential dwellings. Int J Hyg Environ Health 2008;211(1 and 2):114–20.
[10] Takigawa T, Wang BL, Sakano N, Wang DH, Ogino K, Kishi R. A longitudinal study of environmental risk factors for subjective symptoms associated with sick building syndrome in new dwellings. Sci Total Environ 2009;407(19): 5223–8.
[11] Web of Knowledge, ⟨http://apps.webofknowledge.com/summary.do?SID=4B3noxXiCMtclBo26FT&product=WOS&qid=6&search_mode=Refine⟩.
[12] IEEE Xplorer, ⟨http://ieeexplore.ieee.org/Xplore/home.jsp⟩.
[13] Google Scholar, ⟨http://scholar.google.com/⟩.
[14] Envis R. A review of computational optimization methods applied to sustainable building design. Renew Sustain Energy Rev 2013;22:230–45.
[15] Dounis AI, Caraiscos C. Advanced control systems engineering for energy and comfort management in a building environment—a review. Renew Sustain Energy Rev 2009;13:1246–61.
[16] Tuan AN, Marco A. Energy intelligent buildings based on user activity: a survey. Energy Build 2013;56:244–57.
[17] Sadineni SB, Madala S, Boehm RF. Passive building energy savings: a review of building envelope components. Renew Sustain Energy Rev 2011;15(8): 3617–31.
[18] Shameri M, Alghoul M, Sopian K, Zain MFM, Elayeb O. Perspectives of double skin facade systems in buildings and energy saving. Renew Sustain Energy Rev 2011;15(3):1468–75.
[19] Pacheco R, Ordez J, Martnez G. Energy efficient design of building: a review. Renew Sustain Energy Rev 2012;16(6):3559–73.
[20] Baos R, Manzano-Agugliaro F, Montoya F, Gil C, Alcayde A, Gmez J. Optimization methods applied to renewable and sustainable energy a review. Renew Sustain Energy Rev 2011;15(4):1753–66.
[21] Wang J-J, Jing Y-Y, Zhang C-F, Zhao J-H. Review on multi-criteria decision analysis aid in sustainable energy decision-making. Renew Sustain Energy Rev 2009;13(9):2263–78.
[22] Andrea C, Marcus MK, Torrens JI, Edward C. Building operation and energy performance: monitoring, analysis and optimisation toolkit. Appl Energy 2013;101:310–6.
[23] Morosan PD, Bourdais R, Dumur D, Buisson J. Building temperature regulation using a distributed model predictive control. Energy Build 2010;42: 1445–52.
[24] US, Energy Information Administration (⟨http://www.eia.gov/tools/faqs/faq.cfm?id=86&t=1⟩) [accessed 08.10.2013 (US Energy Information Administration)].
[25] EC—European Commission. SEC. 1729, a lead market initiative for Europe. Action plan for sustainable construction, annex I 2007.
[26] EU—European Union. Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings (recast) 2010.
[27] European Parliament and Council. Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings. Official J Eur Union 2010; 53:13–35.
[28] Building Energy Research Center of Tsinghua University.2011 Annual report on China building energy efficiency. Beijing: China Architecture & Building Press; 2011.
[29] Feng YP, Wu Y, Liu CB. Energy-efficiency supervision systems for energy management in large public buildings: necessary choice for China. Energy Policy 2009;37:2060–5.
[30] Jiang P, Tovey NK. Overcoming barriers to implementation of carbon reduction strategies in large commercial buildings in China. Build Environ 2010;45:856–64.
[31] Iran Ministry of Energy. Iran energy balance sheet; 2010.
[32] Balat M. Security of energy supply in Turkey: challenges and solutions. Energy Convers Manage 1998–2011:51.
[33] UNDP. Promoting Energy Efficiency in Buildings in Turkey. 2011–2015, General Directorate of Renewable Energy. ⟨http://www.undp.org.tr/Gozlem2.aspx?WebSayfaNo=2230⟩ [accessed 11.11.2013].
[34] Regulating Authority for Energy (RAE). The energy system in Greece; June 2004.
[35] Perez-Lombarda L, Ortiz J, Pout C. A review on buildings energy consumption information. Energy Build 2008;40:394–8.
[36] ⟨http://www.ssllink.com/mre/cms/mestoZaUploadFajlove/ENERGETSKI_BILANS_PLAN_ZA_2008.pdf⟩ [retrieved 18.05.09].
[37] ⟨http://www.biogasmax.eu/media/biogas_as_vehicle_fuel_in_the_stockholm_region_master_thesis__ellen_martensso__096426600_1216_24092007.pdf⟩ [retrieved 04.07.09].
[38] Barbato A, Carpentieri G. Model and algorithms for the real time management of residential electricity demand. In: Second IEEE ENERGYCON conference & exhibition/future energy grids and systems symposium; 2012. p. 701–6.
[39] U.S. Energy Information Administration. Annual energy review 2009: energy consumption by sector; August 2010.
[40] McQuade JM. A systems approach to high performance buildings. Technical report. United Technologies Corporation; April 2009. ⟨http://gop.science.house.gov/Media/hearings/energy09/april28/mcquade.pdf⟩.
[41] Intelligent Energy Agency (IEA). Policy pathways: energy performance certification of buildings—a policy tool to improve, energy efficiency; 2010.
[42] Singapore Energy Statistics; Policy and Planning Department, Research and Statistics Unit Research and Statistics Unit, Energy Market Authority, Republic of Singapore ISSN 2251-2624; 2012.
[43] Christian M, Carsten B, Mads PN. A cost optimization model for 100% renewable residential energy supply system. Energy 2012;48:118–27.
[44] Taghipour RA, Shams GN, Gharehpetian GB. Robust optimization of distributed generation investment in buildings. Energy 2012;48:455–63.
[45] Hanane D, Riccardo M, Ahmed O, Michela R, Roberto S. Modeling and optimization of a hybrid system for the energy supply of a "Green" building. Energy Convers Manage 2012;64:351–63.
[46] Ferreira PM, Ruano AE, Silva S, Conceicao EZE. Neural networks based predictive control for thermal comfort and energy savings in public buildings. Energy Build 2012;55:238–51.
[47] Anna LP, Michael B, Franco C A. Building energy efficiency optimization method by evaluating the effective thermal zones occupancy. Energies 2012;5: 5257–78.
[48] Bryan E, Zheng ON, Satish N, Vladimir AF, Igor M. A methodology for meta-model based optimization in building energy models. Energy Build 2012;47: 292–301.
[49] Duy LH, Hussein J, Stéphane P, Mireille J. An optimal approach for electrical management problem in dwellings. Energy Build 2012;45:1–14.
[50] Jiří C, Samuel P, Zdeňek V, Evaˇ Z, Lukǻs F. Optimization of predicted mean vote index within model predictive control framework: computationally tractable solution. Energy Build 2012;52:39–49.
[51] Ion H, Christian G, David P. Optimal temperature control of intermittently heated buildings using model predictive control. Part II e Control algorithm. Build Environ 2012;51:388–94.
[52] Laura K, Jun-young K, Geoffrey K, Farrokh J, Burcin B-G, Pradeep V, et al. Coordinating occupant behavior for building energy and comfort management using multi-agent systems. Autom Constr 2012;22:525–36.
[53] Wang Z, Wang L, Dounis AI, Yang R. Multi-agent control system with information fusion based comfort model for smart buildings. Appl Energy 2012;99:247–54.
[54] Zhoua D, Park SH. Simulation-assisted management and control over building energy efficiency—a case study. In: Proceedings energy procedia, vol. 14; 2012. p. 592–600.
[55] Yang R, Wang L. Optimal control strategy for HVAC system in building energy management. In: Procedings transmission and distribution conference and exposition (T&D), IEEE PES; 2012. p. 1–8.
[56] Wang Z, Wang L. Occupancy pattern based intelligent control for improving energy efficiency in buildings. In: Procedings of the eighth IEEE international conference on automation science and engineering, Seoul, Korea; August 20–24, 2012. p. 804–9.
[57] Missaoui R, Warkozek G, Bacha S, Ploix S. Real time validation of an optimization building energy management strategy based on power-hardware-in-the-loop tool. In: Procedings of the third IEEE PES innovative smart grid technologies Europe (ISGT Europe), Berlin; 2012. p. 1–7.
[58] Jingran M, Qin SJ, Salsbury T. Model predictive control of building energy systems with balanced model reduction. In: Proceedings of the American control conference Fairmont Queen Elizabeth, Montréal, Canada; June 27–June 29, 2012. p. 3681–6.
[59] Bozchalui MC, Sharma R. Optimal operation of commercial building microgrids using multi-objective optimization to achieve emissions and efficiency targets. In: Proceedings of the power and energy society general meeting, IEEE; 2012. p. 1–8.
[60] Cigler J, Pr´ıvara S, V˘ǎna Z, Kom´arkov´ D, Michael S. Optimization of predicted mean vote thermal comfort index within model predictive control framework. In: Proceedings of the 51st IEEE conference on decision and control, Maui, HI, USA; December 10–13, 2012. p. 3056–61.
[61] Asare-Bediako B, Ribeiro PF, Kling WL. Integrated energy optimization with smart home energy management systems. In: Proceedings of the third IEEE PES innovative smart grid technologies Europe (ISGT Europe), Berlin; 2012. p. 1–8.
[62] Wang Z, Wang L. Indoor air quality control for energy-efficient buildings using CO_2 predictive model. In: Proceedings of the industrial informatics (INDIN), 10th IEEE international conference; 2012. p. 133–8.
[63] Wang L, Wang Z, Yang R. Intelligent multi-agent control system for energy and comfort management in smart and sustainable buildings. Proceedings IEEE Trans Smart Grid 2012;3(2):605–17.
[64] Gerhard Zucker, Tarik Ferhatbegovic, Dietmar Bruckner, Building automation for increased energy efficiency in buildings. In: Proceedings of the industrial electronics (ISIE), IEEE international symposium; 2012. p. 1191–1196.

[65] Raghunathan Arvind U., Krishnamurthy Sudha. Distributed anytime algorithm for maximizing occupant comfort. In: Proceedings of the 2012 American control conference Fairmont Queen Elizabeth, Montréal, Canada; June 27–June 29, 2012. p. 1059–66.
[66] Anthony K, Yudong M, Francesco B. Analysis of local optima in predictive control for energy efficient buildings. In: Proceedings of the 50th IEEE conference on decision and control and European control conference (CDC-ECC) Orlando, FL, USA; December 12–15, 2011. p. 5125–30.
[67] Anthony K, Francesco B. Parallel nonlinear predictive control. In: Proceedings of the fiftieth annual Allerton conference Allerton House, UIUC, IL, USA; October 1–5, 2012. p. 71–8.
[68] Barbato A, Capone A, Carello G, Delfanti M, Merlo M, Zaminga A. House energy demand optimization in single and multi-user scenarios. In: Proceedings of the smart grid management and service design; 2011. p. 345–350.
[69] Vangelis M, Haris D, Charikleia K, John P. An integrated system for buildings' energy-efficient automation: application in the tertiary sector. Appl Energy 2013;101:6–14.
[70] Victor MZ. Real-time optimization strategies for building systems. Ind Eng Chem Res 2013;52:3137–50.
[71] Florent B, Mohamed E-M, Michel P. Genetic algorithms based optimization of artificial neural network architecture for buildings' indoor discomfort and energy consumption prediction. Build Simul 2012;5:95–106.
[72] Alvarez JD, Redondo JL, Camponogara E, Normey-Rico J, Berenguel M, Ortigosa PM. Optimizing building comfort temperature regulation via model predictive control. Energy Build 2013;57:361–72.
[73] Antonio C-S, Lya NTL, David B-D, Manuel C-G. Solutions to reduce energy consumption in the management of large buildings. Energy Build 2013;56:66–77.
[74] Peng Z, Siddharth S, Marcelo GS. An energy management system for building structures using a multi-agent decision-making control methodology. IEEE Trans Ind Appl 2013;49(1):322–30.
[75] Hao L, Qianchuan Z, Ningjian H, Xiang Z. A simulation based tool for energy efficient building design for a class of manufacturing plants. IEEE Trans Autom Sci Eng 2013;10(1):117–23.
[76] Diogenes M, Coby L, Viktoriya S, Ronald GH. Model predictive and genetic algorithm-based optimization of residential temperature control in the presence of time-varying electricity prices. IEEE Trans Ind Appl 2013;49(3): 1137–45.
[77] Wang Z, Wang L. Intelligent control of ventilation system for energy-efficient buildings with CO_2 predictive model. Proc IEEE Trans Smart Grid 2013;4(2): 686–93.
[78] Raziei SA, Mohsenian-Rad H. Optimal demand response capacity of automatic lighting control. In: Proceedings of the innovative smart grid technologies (ISGT); 2013. p. 1–6.
[79] Wang Z, Yang R, Wang L. Multi-agent intelligent controller design for smart and sustainable buildings. In: Proceedings of the fourth annual IEEE systems conference; 2010. p. 277–282.
[80] Wang Z, Yang R, Wang L. Multi-agent control system with intelligent optimization for smart and energy-efficient buildings. In: Proceedings of the 36th annual conference on IEEE Industrial Electronics Society IECON; 2010. p. 1144–9.
[81] Wang Z, Yang R, Wang L. Intelligent multi-agent control for integrated building and micro-grid systems. In: Proceedings of the innovative smart grid technologies (ISGT); 2011. p. 1–7.
[82] Benjamin Paris, Julien Eynard, Stéphane Grieu, Monique Polit. Hybrid PID-fuzzy control scheme for managing energy resources in buildings. Appl Soft Comput 2011;11:5068–80.
[83] Husen SA, Pandharipande A, Tolhuizen L, Wang Y, Zhao M. Lighting systems control for demand response. In: Proceedings of the innovative smart grid technologies (ISGT); 2012. p. 1–6.
[84] Fehmi GU, Yukseltan E. A linear programming approach to household energy conservation: efficient allocation of budget. Energy Build 2012;49:200–8.
[85] Jian L, Jae YC, Jin X, James W-KH, Raouf B. On the design and implementation of a home energy management system. In: Proceedings of the sixth international symposium on wireless and pervasive computing (ISWPC); 2011. p. 1–6.
[86] Dounis AI, Caraiscos C. Intelligent coordinator of fuzzy controller-agents for indoor environment control in buildings using 3-D fuzzy comfort set. In: Proceedings of the IEEE international fuzzy systems conference; 2007. p. 1–6.
[87] Kolokotsa D, Stavrakakis GS, Kalaitzakisb K, Agoris D. Genetic algorithms optimized fuzzy controller for the indoor environmental management in buildings implemented using PLC and local operating networks. Eng Appl Artif Intell 2002;15:417–28.
[88] Duy LH, Stephane P, Eric Z, Mireille J. A home automation system to improve household energy control. In: Proceedings of the 12th IFAC symposium on information control problems in manufacturing INCOM; 2006. p. 5–17.
[89] Zhe Y, Linda M, Liyan J, Mary CM-H, Annabelle P, Lang T. Modeling and stochastic control for home energy management. In: Proceedings of the, submission to PES'12. 11/28/11**.
[90] Bei L, Siddharth G, Samuel C, Pramode KV. Predicting user comfort level using machine learning for smart grid environments. In: Proceedings of the innovative smart grid technologies (ISGT); 2011. p. 1–6.
[91] Yang R, Wang Z, Wang L. A GUI-based simulation platform for energy and comfort management in zero-energy buildings. In: Proceedings of the North American power symposium (NAPS); 2011.p. 1–7.
[92] Yang R, Wang L. Multi-objective optimization for decision-making of energy and comfort management in building automation and control. Sustain Cities Soc 2012;2:1–7.
[93] Yang R, Wang L. Multi-zone building energy management using intelligent control and optimization. Sustain Cities Soc 2013;6:16–21.
[94] Haris D, Konstantinos DP, Konstantinos I, John P. Intelligent building energy management system using rule sets. Building Environ 2007;42:3562–9.
[95] Mahdavi A, Mahattanatawe P. Enclosure systems design and control support via dynamic simulation-assisted optimization. In: Proceedings of the building simulation; 2003.
[96] Kampf JH, Robinson D. Optimization of urban energy demand using an evolutionary algorithm. In: Proceedings of the building simulation; 2009.
[97] Palonen M, Hasan A, Siren K. A genetic algorithm for optimization of building envelope and HVAC system parameters. In: Proceedings of the building simulation; 2009.
[98] Huang H, Kato S, Hu R. Optimum design for indoor humidity by coupling genetic algorithm with transient simulation based on contribution ratio of indoor humidity and climate analysis. Energy Build 2012;47:208–16.
[99] Ghisi E, Tinker J. Optimizing energy consumption in offices as a function of window area and room size. In: Proceedings of the building simulation; 2001.
[100] Wetter M, Polak E. A convergent optimization method using pattern search algorithmswith adaptive precision simulation. In: Proceedings of the eighth international IBPSA conference, Eindhoven, Netherlands; 2003. p. 1393–400.
[101] Wetter M, Polak E. Building design optimization using a convergent pattern search algorithm with adaptive precision simulations. Energy Build 2005:37.
[102] Wetter M. Modelica-based modelling and simulation to support research and development in building energy and control systems. J Build Perform Simul 2009;2(2):143–61.
[103] Park C-S, Augenbroe G, Messadi T. Day lighting optimization in smart facade systems. In: Proceedings of the building simulation; 2003.
[104] Yoon S-H, Park C-S, Augenbroe G. On-line parameter estimation and optimal control strategy of a double-skin system. Build Environ 2011;46(5):1141–50.
[105] Evins R, Pointer P, Vaidyanathan R, Multi-objective optimization of the configuration and control of a double-skin facade. In: Proceedings of the building simulation; 2011.
[106] Wetter M, Haves P. A modular building controls virtual test bed for the integrations of heterogeneous systems. In: Third national conference of IBPSA-USA, Berkeley, CA, USA: IBPSA-USA; 2008. p. 69–78.
[107] Wright J, Loosemore H, Farmani R. Optimization of building thermal design and control by multi-criterion genetic algorithm. Energy Build 2002;34: 959–72.
[108] Wright J, Farmani R. The simultaneous optimization of building fabric construction, HVAC system size, and the plant control strategy. In: Proceedings of the building simulation; 2001.
[109] Fong K, Hanby V, Chow T. HVAC system optimization for energy management by evolutionary programming. Energy Build 2006;38:220–31.
[110] Lee K-P, Cheng T-A. A simulation–optimization approach for energy efficiency of chilled water system. Energy Build 2012;54:290–6.
[111] Congradac V, Kulic F. Recognition of the importance of using artificial neural networks and genetic algorithms to optimize chiller operation. Energy Build 2012;47:651–8.
[112] Safdar A, DoHyeun K. Energy conservation and comfort management in building environment. Int J Innov Comput Inf Control 2013;9(6):2229–44.
[113] Lu L, Cai W, Xie L, Li S, Soh YC. HVAC system optimization in-building section. Energy Build 2005;37(1):11–22.
[114] Huang W, Lam H. Using genetic algorithms to optimize controller parameters for HVAC systems. Energy Build 1997;26:277–82.
[115] De Ridder F, Diehl M, Mulder G, Desmedt J, Van Bael J. An optimal control algorithm for borehole thermal energy storage systems. Energy Build 2011;43 (10):2918–25.
[116] Peippo K, Lund PD, Vartiainen E. Multivariate optimization of design trade-offs for solar low energy buildings. Energy Build 1999;29(2):189–205.
[117] Salminen M, Palonen M, Siren K. Combined energy simulation and multi-criteria optimisation of a LEED-certified building. In: Proceedings of the building simulation and optimization conference; 2012.
[118] Griego D, Krarti M, Hernndez- Guerrero A. Optimization of energy efficiency and thermal comfort measures for residential buildings in Salamanca, Mexico. Energy Build 2012;54:540–9.
[119] Hamdy M, Hasan A, Siren K. Combination of optimisation algorithms for a multi-objective building design problem. In: Proceedings of the building simulation; 2009.
[120] Hamdy M, Palonen M, Hasan A. Implementation of pareto-archive NSGA-II algorithms to a nearly zero energy building optimization problem. In: Proceedings of the building simulation and optimization conference; 2012.
[121] Siddharth V, Ramakrishna P, Geetha T, Sivasubramaniam A. Automatic generation of energy conservation measures in buildings using genetic algorithms. Energy Build 2011;43(10):2718–26.
[122] Kastner W, Kofler MJ, Reinisch C. Using AI to realize energy efficient yet comfortable smart homes. In: Proceedings of the eighth IEEE international workshop on factory communication systems (WFCS '10) 2010:169–72.
[123] Mozer M. The neural network house: an environment that adapts to its inhabitants, In: Coen M, editor, Proceedings of the American Association for artificial intelligence spring symposium on intelligent environments; 1998. p. 110–4.
[124] Davidsson P, Boman M. Distributed monitoring and control of office buildings by embedded agents. Inf Sci 2005;171:293–307.
[125] Delaney DT, Hare GMPO, Ruzzelli AG. Evaluation of energy-efficiency in lighting systems using sensor networks. In: Proceedings of the first ACM

workshop on embedded sensing systems for energy-efficiency in buildings; 2009. p. 61–6.
[126] Erickson VL, Lin Y, Kamthe A, Rohini B, Surana A, Cerpa AE, et al. Energy efficient building environment control strategies using real time occupancy measurements. In: Proceedings of the first ACM workshop on embedded sensing systems for energy-efficiency in buildings; 2009. p. 19–24.
[127] Erickson VL, Cerpa AE. Occupancy based demand response HVAC control strategy. In: Proceedings of the second ACM workshop on embedded sensing systems for energy-efficiency in building; 2010. p. 7–12.
[128] Singhvi V, Krause A, Guestrin C, Garrett Jr JH, Matthews HS. Intelligent light control using sensor networks. In: Proceedings of the third international conference on embedded networked sensor systems; 2005. p. 218–29.
[129] Dong B, Andrew B. Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings. In: Proceedings of the building simulation; 2009.
[130] Chen H, Chou P, Duri S, Lei H, Reason J. The design and implementation of a smart building control system. In: Proceedings of the IEEE international conference on e-business engineering; 2009. p. 255–62.
[131] Pfafferott JU, Herkel S, Kalz DE, Zeuschner A. Comparison of low-energy office buildings in summer using different thermal comfort criteria. Energy Build 2007;39(7):750–7.
[132] Wen YJ, Agogino A. Wireless networked lighting systems for optimizing energy savings and user satisfaction. In: Proceedings of the IEEE wireless hive networks conference; 2008. p. 1–7.
[133] Dong B, Lam KP, Neuman CP., Integrated building control based on occupant behavior pattern detection and local weather forecasting. In: Proceedings of the 12th conference of international building performance simulation association, Sydney, Australia; 2011.
[134] Georgievski I, Degeler V, Pagani GA, Nguyen TA, Lazovik A, Aiello M. Optimizing energy costs for offices connected to the smart grid. Proc IEEE Trans Smart Grids 2012;3(4):2273–85.
[135] Wang Z, Tan YK. Illumination control of LED systems based on neural network model and energy optimization algorithm. Energy Build 2013;62:514–21.
[136] Goyal S, Ingley Herbert A, Barooah P. Occupancy-based zone-climate control for energy-efficient buildings: complexity vs. performance. Appl Energy 2013;106:209–21.
[137] Wang N, Zhang J, Xia X. Desiccant wheel thermal performance modeling for indoor humidity optimal control. Appl Energy 2013;112:999–1005.
[138] Fischer JC, Bayer Charlene W. Humidity control in school facilities. Energy 2003;30:35.
[139] Shadi A, Ploix S, Pesty S, Jacomino M. A multi-agent home automation system for power management. In: Proceedings of the informatics in control automation and robotics; 2008. p. 59–68.
[140] Bojic´ M, Nikolic´ N, Nikolic´ D, Skerlic´ J, Miletic I. Toward a positive-net-energy residential building in Serbian conditions. Appl Energy 2011;88: 2407–19.
[141] Wang S, Xu X. A robust control strategy for combining DCV control with economizer control. Energy Convers Manage 2002;43:2569–88.
[142] Wang S, Xu X. Optimal and robust control of outdoor ventilation airflow rate for improving energy efficiency and IAQ. Build Environ 2004;39:763–73.
[143] Wang S, Jin X. Model-based optimal control of VAV air-conditioning system using genetic algorithms. Build Environ 2000;35:471–87.
[144] Kummert M, Andre P, Nicolas J. Optimal heating control in a passive solar commercial building. Solar Energy 2001;69(1–6):103–16.
[145] Morel N, Bauer M, El-Khoury Krauss J. Neurobat, a predictive and adaptive heating control system using artificial neural networks. Int J Solar Energy 2000;21:161–201.
[146] Lopez L, Sanchez, Doctor F, Hagras H, Callaghan V. An evolutionary algorithm for the off-line data driven generation of fuzzy controllers for intelligent buildings. In: Proceedings of the IEEE international conference on Systems, man and cybernetics, vol. 1; 2004. p. 42–7.
[147] Dounis AI, Manolakis DE. Design of a fuzzy system for living space thermal comfort regulation. Appl Energy 2001;69:119–44.
[148] Calvino F, Gennusca ML, Rizzo G, Scaccianoce G. The control of indoor thermal comfort conditions: introducing a fuzzy adaptive controller. Energy Build 2004;36:97–102.
[149] Liang J, Du R. Thermal comfort control based on neural network for HVAC application. In: Proceedings of the IEEE conference on control applications CCA; 2005. p. 819–24.
[150] Guillemin A, Morel N. An innovative lighting controller integrated in a self-adaptive building control system. Energy Build 2001;33(5):477–87.
[151] Guillemin A, Molteni S. An energy-efficient controller for shading devices self-adapting to the user wishes. Build Environ 2002;37:1091–7.
[152] Kolokotsa D, Tsiavos D, Stavrakakis G, Kalaitzakis K, Antonidakis E. Advanced fuzzy logic controllers design and evaluation for buildings' occupants thermal-visual comfort and indoor air quality satisfaction. Energy Build 2001;33(6):531–43.
[153] Kolokotsa D. Comparison of the performance of fuzzy controllers for the management of the indoor environment. Build Environ 2003;38:1439–50.
[154] Rutishauser U, Joller J, Douglas R. Control and learning of ambience by an intelligent building. IEEE Trans Systems Man Cybernet. Part A Syst Humans 2005;35(1):121–32.
[155] Lah MT, Borut Z, Krainer A. Fuzzy control for the illumination and temperature comfort in a test chamber. Build Environ 2005;40:1626–37.
[156] Lah MT, Borut Z, Peternelj J, Krainer A. Daylight illuminance control with fuzzy logic. Solar Energy 2006;80:307–21.
[157] Hamdi M, Lachiever G. A fuzzy control system based on the human sensation of thermal comfort. In: Proceedings of the fuzzy systems IEEE world congress on computational intelligence, vol. 1; 1998. p. 487–92.
[158] Yamada F, Yonezawa K, Sugarawa S, Nishimura N. Development of air conditioning control algorithm for building energy-saving. In: Proceedings of the IEEE international conference on control applications; 1999.
[159] Huang W, Lam H. Using genetic algorithms to optimize controller parameter for HVAC systems. Energy Build 1997;26(3):277–82.
[160] Ari S, Cosden IA, Khalifa HE, Dannenhoffer JF, Wilcoxen P, Isik C. Constrained fuzzy logic approximation for indoor comfort and energy optimization. In: Proceedings of the annual conference of the North American fuzzy information processing society—NAFIPS; 2005. p. 500–4.
[161] Alcala R, Benitez JM, Casillas J, Cordon O, Perez R. Fuzzy control of HVAC systems optimized by genetic algorithms. Appl Intell 2003;18:155–77.
[162] Lam HN. Intelligent computer control of air conditioning systems based on genetic algorithms and classifier system. Build Simul 1995:151–7.
[163] Dalamagkidis K, Kolokotsa D, Kalaitzakis K, Stavrakakis GS. Reinforcement learning for energy conservation and comfort in buildings. Build Environ 2007;42(7):2686–98.
[164] Bernard C, Guerrier B, Rasset-Louerant MM. Optimal building energy management. Part II: control. ASME J Solar Energy Eng 1982;114:13–22.
[165] Levermore GJ. Building energy management systems: an application to heating and control. London: E & FN SPON; 1992.
[166] Mathews EH, Arndt DC, Piani CB, Heerden E. Developing cost efficient control strategies to ensure optimal energy use and sufficient indoor comfort. Appl Energy 2000;66:135–59.
[167] Salsbury TI. A temperature controller for VAV air-handing units based on simplified physical models. HVAC&R Res 1998;3(3):264–79.
[168] Kasahara M, Matsuba T. Design and tuning of robust PID controller for HVAC systems. Proc ASHRAE Trans 1999;105(2):154–66.
[169] Ang KH, Chong GCY, Li Y. PID control system analysis, design, and technology. IEEE Trans Control Syst Technol 2005;13(4):559–76.
[170] Li Y, Ang KH, Chong GCY. PID control system analysis and design—problems, remedies, and future directions. IEEE Control Syst Mag 2006;26(1):32–41.
[171] Kaya I, Tan N, Atherton DP. Improved cascade control structure for enhanced performance. J Process Control 2007;17(1):3–16.
[172] Thomas B, Soleimani-Mohseni M, Fahlen P. Feed-forward in temperature control in buildings. Energy Build 2005;37(7):755–61.
[173] Zaheer-Uddin M, Zheng GR. Optimal control of time scheduled heating, ventilating and air conditioning processes in buildings. Energy Convers Manage 2000;41:49–60.
[174] Chen T. Real-time predictive supervisory operation of building thermal systems with thermal mass. Energy Build 2001;33:141–50.
[175] Henze GP, Dodier RH, Krarti M. Development of a predictive optimal controller for thermal energy storage systems. HVAC&R Res 1997;3(3): 233–64.
[176] Curtis PS, Shavit G, Kreider K. Neural networks applied to buildings—a tutorial and case studies in prediction and adaptive control. Proc ASHRAE Trans 1996;102:1.
[177] Mozer MC, Vidmar L, Dodier RH. The neuro thermostat: predictive optimal control of residential heating systems. Proceedings of advances in neural information processing systems, 9. Cambridge, MA: MIT Press; 1997; 953–9.
[178] Gouda MM, Danaher S, Underwood CP. Quasi-adaptive fuzzy heating control of solar buildings. Build Environ 2006;41:1881–91.
[179] Nesler CG. Adaptive control of thermal processes in buildings. IEEE Control Syst Mag 1986;6(4):9–13.
[180] Teeter J, Chow MY. Application of functional link neural network to HVAC thermal dynamic system identification. IEEE Trans Ind Electron 1998;45 (1):170–6.
[181] Lute PJ, Paassen VAHPredictive control of indoor temperatures in office buildings energy consumption and comfort. In: Proceedings of 2000; 1989.
[182] Paassen AH, Liem SH, Lute PJ. Digital control systems for passive solar buildings. In: CEC-Project Pastor; 1990.
[183] Milanic S, Karba R. Neural network models for predictive control of a thermal plant. In: Proceedings of the international conference on EANN'96; 1996. p. 151–4.
[184] Gouda M, Danaher S, Underwood C. Thermal comfort based fuzzy logic controller. Build Serv Eng Res Technol 2001;22(4):237–53.
[185] Guillemin A, Morel N. An innovative lighting controller integrated in a self-adaptive building control system. Energy Build 2001;33:477–87.
[186] Eftekhari M, Marjanovic L, Angelov PP. Design and performance of a rule based controller in a naturally ventilated room. Comput Ind 2003;51:299–326.
[187] Ketata R. Méthodologies de régulation numérique incluant la logique floue [Thèse de Doctorat INSA]. Toulouse, France: LAAS; 1992.
[188] Ben-Nakhi AE, Mahmoud MA. Energy conservation in buildings through efficient A/C control using neural networks. Appl Energy 2001;73:5–23.
[189] Kazanasmaz T, Günaydin M, Binol S. Artificial neural networks to predict daylight illuminance in office buildings. Build Environ 2009;44(8):1751–7.
[190] Karatasou S, Santamouris M, Geros V. Modeling and predicting building's energy use with artificial neural networks: methods and results. Energy Build 2006;38(8):949–58.
[191] Ma Y, Borrelli F, Hencey B, Packard A, Bortoff S. Model predictive control of thermal energy storage in building cooling systems. In: Proceedings of the 48th IEEE conference on decision and control, Shanghai, China; 2009. p. 392–7.
[192] Yuan S, Perez R. Multiple-zone ventilation and temperature control of a single duct VAV system using model predictive strategy. Energ Build 2006;38:1248–61.

[193] Duburcq S, Guillerminet S. Advanced control for intermittent heating. In: Proceedings of Clima 2000 conference, Brussels, Belgium; 1997.
[194] Karlsson H, Hagentoft C-E. Application of model based predictive control for water-based floor heating in low energy residential buildings. Build Environ 2011;46:556–69.
[195] Gyalistras D, Gwerder M. Use of weather and occupancy forecasts for optimal building climate control (OptiControl): two years progress report. Zug, Switzerland: Terrestrial Systems Ecology ETH and Building Technologies Division, Siemens Switzerland Ltd.; 2010.
[196] Ghiaus C, Hazyuk I. Calculation of optimal thermal load of intermittently heated buildings. Energy Build 2010;42:1248–58.
[197] Kummert M, Leduc M-A, Moreu A. Using MPC to reduce the peak demand associated with electric heating. Model predictive control in buildings workshop, Montreal; 2011.
[198] Lee K-H, Braun JE. Model-based demand-limiting control of building thermal mass. Build Environ 2008;43:1633–46.
[199] Oldewurtel F, Parisio A, Jones C, Morari M, Gyalistras D, Gwerder M, et al. Energy efficient building climate control using stochastic model predictive control and weather predictions. In: Proceedings of American control conference; 2010.
[200] Chen T. Application of adaptive predictive control to a floor heating system with a large thermal lag. Energy Build 2002;34(1):45–51.
[201] Ma Y, Kelman A, Daly A, Borrelli F. Predictive control for energy efficient buildings with thermal storage: modeling, stimulation, and experiments. IEEE Control Syst 2012;32(1):44–64.
[202] Lamoudi M, Alamir M, Béguery P. Distributed constrained model predictive control based on bundle method for building energy management. In: Proceedings of the IEEE conference on decision and control, Orlando, FL, USA; 2011, p. 8118–24.
[203] Dounis AI. Artificial intelligence for energy conservation in buildings. Adv Build Energy Res 2010;4:267–99.
[204] Scerri P, Pynadath DV, Tambe M. Towards adjustable autonomy for the real world. J Artif Intell Res 2002;17:171–228.
[205] Joumaa H, Ploix S, Abras S, De Oliveira G A. MAS integrated into Home automation system, for the resolution of power management problem in smart homes. Energy Procedia: Elsevier Ltd. 2011;6:786–94.
[206] Ramchum SD, Vytelingum P, Rogers A, Jennings N. Agent-based control for the decentralized demand side management in the smart grid. Autonomous Agents Multi-agent Syst 2011;1:5–12.
[207] Jun Z, Jie W, Liu Jun-feng, Gao La-mei, Min L. An agent-based approach to renewable energy management in eco-building. Proc IEEE 2008:46–50.
[208] Lee J. Conflict resolution in multi-agent based intelligent environments. Build Environ 2010;45:574–85.
[209] Qiao B, Liu K, Guy C. Multi-agent building control in shared environment. IEEE International Conference on Fuzzy Systems (In; IEEE World Congress on Computational Intelligence), INSTICC Press. AIDSS; 2007, 159–164.
[210] Hagras H, Packharn I, Vanderstockt Y, McNulty N, Vadher A, Doctor F. An intelligent agent based approach for energy management in commercial buildings. Proc IEEE 2008:156–62.
[211] Azar E, Menassa C. An agent-based approach to model the effect of occupants' energy use characteristics in commercial buildings. In: Proceedings of the American Society of Civil Engineers (ASCE); 2011. p. 536–43.
[212] Abras S, Ploix S, Pesty S, Jacomino M. A multi-agent design for a home automation system dedicated to power management. In: Proceedings of the fourth conference on artificial intelligence innovations & applications, Athens, Greece; 2007. p. 19–21.
[213] Musliner D, Pell B, editors. Agents with adjustable autonomy, AAAI spring symposium. Technical report SS-99-06, AAAI; 1999. ISBN 1-57735-102-9.
[214] Baños R, Manzano-Agugliaro F, Montoya FG, Gil C, Alcayde A, Gómez J. Optimization methods applied to renewable and sustainable energy: a review. Renew Sustain Energy Rev 2011;15(4):1753–66.
[215] Storn R, Price K. Differential evolution a simple and efficient heuristic for global optimization over continuous spaces. J Global Optim 1997;11(4): 341–59.
[216] Sette S, Boullart L. Genetic programming: principles and applications. Eng Appl Artif Intell 2001;14(6):727–36.
[217] US Department of Energy, Energy Efficiency and Renewable Energy, ⟨http://apps1.eere.energy.gov/buildings/tools_directory/subjects.cfm/pagename=subjects/pagename_menu=whole_building_analysis/pagename_submenu=energy_simulation⟩.
[218] The MathWorks. MATLAB program v. Natick, MA: The Math Works, Inc.; 2012; 2012.
[219] Hensen JLM. A comparison of coupled and de-coupled solution for temperature and airflow in a building. Proc ASHRAE Trans 1999;105(2):962–9.
[220] Transient System Simulation (TRNSYS) Tool, ⟨http://www.trnsys.com/⟩.
[221] Zhou G, Ihm P, Krarti M, Liu S, Henze GP. Integration of a internal optimization module within EnergyPlus. Proceedings of the eighth international IBPSA conference. Eindhoven: IBPSA; 2003; 1475–82.
[222] Monjour MM, Kelliher D, Keane M. ArDOT: a tool to optimize environmental design of buildings. In: Augenbroe G, Hensen J, editors. Proceedings: eighth international IBPSA conference. Eindhoven: IBPSA; 2003. p. 919–26.
[223] Christensen C, Anderson R, Horowitz S, Courtney A, Spencer J. BEopt software for building energy optimization: features and capabilities. Technical report NREL/TP-550-39929. Boulder: National Renewable Energy Laboratory/University of Colorado; 2006.
[224] NREL. Opt-E-Plus Software for commercial building optimization (Fact Sheet). Golden, CO: NREL: National Renewable Energy Laboratory; 2010.
[225] Attia S, Gratia E, De Herde A, Hensen J. Simulation-based decision support tool for early stages of zero-energy building design. Energy Build 2012;49: 2–15.
[226] Pan Y, Lin X, Huang Z, Sun J, Ahmed O. A verification test bed for building control strategy coupling TRANsys with a real controller. In Proceedings of the building simulation: 12th conference of international building performance simulation association, Sydney; November 2011.
[227] Klemm K, Marks W, Klemm AJ. Multicriteria optimisation of the building arrangement with application of numerical simulation. Build Environ 2000;35(6):537–44.
[228] Schneider Electric, ⟨http://www.schneider-electric.com/solutions/ww/en/seg/27947930-smart-cities/27957983-smart-buildings-homes⟩ [accessed on 17.11.2013].
[229] Ramesh S., http://ifonlysingaporeans.blogspot.com/2012/06/singapores-strategy-to-fight-climate.html [accessed on July 2012].